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Impact of Land Use and Land Cover Changes on Ecosystem Services in the Upper Awash River Basin, Central Ethiopia. A Path to Sustainability

By

Fekadu Legesse

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APPROVAL PAGE

I, the undersigned, declare that this thesis is based on my original work and that it has not been presented for a degree in any other university. All sources of materials have been duly acknowledged.

Fekadu Legesse ______________________ June 2025

This thesis has been submitted for examination with my approval as supervisor of the dissertation.

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This is to certify that the thesis presented by Fekadu Legesse entitled: **“Impact of Land Use and Land Cover Changes on Ecosystem Services in the Upper Awash River Basin, Central Ethiopia. A Path to Sustainability”** and a dissertation submitted to the center for environmental science in partial fulfillment of the requirements for the degree of doctor of philosophy in environmental science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

Land use and land cover changes have a significant impact on ecosystem services, which can potentially contribute to long-term climate change. This study evaluates the effects of Land Use and Land Cover (LULC) changes on ecosystem services in the Upper Awash River Basin from 1993 to 2023. Land use and land cover maps for each period were generated from Landsat images in ArcGIS. The study adopted image processing and a supervised classification approach using the maximum likelihood classifier. The accuracy of LULC classifications was evaluated using error matrices derived from ground truth points. A stratified systematic sampling design was applied using 10 m × 20 m rectangular plots, with the number of plots determined by the size and type of land use. A total of 498 plots were established to assess carbon stocks and environmental parameters. In forest and shrubland plots, trees and shrubs with a DBH ≥ 5 cm were measured, while soil samples were collected from 1 m² subplots within the main plots across all four land use types. Remote sensing, ArcGIS, and the InVEST model were used to map changes in LULC, carbon stock and Ecosystem Services Value (ESV). The current carbon stocks in the basin were calculated using a linear regression model, with the Enhanced Vegetation Index (EVI) proving to be the more reliable indicator for calculating carbon stocks than other indices (NDVI and SAVI) due to its ability to minimize the effects of soil, atmosphere, and background noise. The overall ESV for the basin were computed using global coefficient values. The results from LULC analysis demonstrated that forestland, shrubland, and wetland areas experienced substantial declines of 27.4%, 41.6%, and 60.6%, respectively, while cropland and built-up areas expanded by 9% and 154%. These shifts in land cover are primarily driven by agricultural expansion, urbanization, and socio-economic factors such as population growth and poverty. This led to a 15% decrease in the overall carbon stock of the basin from 17.3 million tons in 1993 to 14.8 million tons in 2023. The estimated carbon stock from the developed EVI linear regression model was 15,904,158.24 tons, with an average carbon stock value of 111.96 tons per hectare. The study also found a 13.14% decrease in the ESV over the study period, amounting to a loss of US$ 227.54 million.

While provisioning ecosystem services (such as food and water supply) increased by $37.25 million, regulating services (carbon sequestration and water regulation) saw a substantial decrease of $194.58 million. This highlights the trade-offs between land use for agriculture and the long-term environmental benefits that ecosystems provide. The study found that the ESV was relatively insensitive to land-use changes, as the sensitivity coefficients were all less than one. This suggests that while LULC changes impact ecosystem services, the overall effect remains stable. The basin's transformation due to LULC changes is a critical concern that intertwines environmental sustainability with socioeconomic stability. Thus, the findings offer valuable insights for policymakers, environmental agencies, land management authorities, and local communities in the Basin. These insights can guide sustainable land use practices by strengthening land use planning, promoting afforestation and reforestation, biodiversity conservation, climate change mitigation, ecosystem restoration, and improvements to local community well-being.

Keywords: ArcGIS, Awash River Basin, Carbon Stock, Ecosystem Services Value, Land Use Land Cover, Sustainable Land Management, Vegetation Index

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Table of Contents

List of Tables

List of Figures

Acronyms

AGB	Above-Ground Biomass
AGC	Above-ground carbon
BGB	Below-Ground Biomass
BGC	Below Ground Carbon
BD	Bulky Density
CBD	Convention on Biological Diversity
CS	Coefficient of Sensitivity
NDVI	Normalized Difference Vegetation Index
ESV	Ecosystem Services Value
EVI	Enhanced Vegetation Index
GPS	Geographical Position System
GHG	Greenhouse Gas
GIS	Geographic Information System
InVEST	Integrated Valuation of Ecosystem Services and Tradeoff
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land Cover
MEA	Millennium Ecosystem Assessment
NIR	Near-Infrared
PA	Producer Accuracy
RS	Remote Sensing
SAVI	Soil-Adjusted Vegetation Index
SDGs	Sustainable Development Goals
SOC	Soil Organic Carbon
TEEB	The Economics of Ecosystems and Biodiversity
UA	User Accuracy
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United States Geological Survey
Vis	Vegetation Indices

List of Publications

- Carbon stock dynamics in a changing land use land cover of the Upper Awash River Basin: Implications for climate change management

  http://dx.doi.org/10.1080/27658511.2024.2361565

- Quantifying Ecosystem Service Values Amid Land Use and Land Cover Transformation in the Upper Awash River Basin: A Path toward Climate Change Mitigation
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- Estimating carbon stock using vegetation indices and empirical data in the Upper Awash River
  https://link.springer.com/article/10.1007/s44274-024-00165-8
- Ecological and Economic Impacts of REDD+ Implementation in Developing Countries
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CHAPTER ONE

1. INTRODUCTION

1.1. BACKGROUND

Climate change and global warming pose significant threats to global ecosystems because they impact the characteristics of ecosystems and energy and material flows (Geest et al., 2019; Markham, 1996). These changes affect nutrients and biodiversity. The cause of climate change is the rise in GHG emissions, particularly CO_2, due to human actions, including burning of fossil fuels, forest deforestation, and industrial developments (Javaherian et al., 2021). The concentration of CO_2 in the lower atmosphere has surpassed preindustrial levels, with CO_2 being one of the major GHGs (Brown, 2002). The release of these gases' traps heat in the Earth's atmosphere, warming the planet.

Enhancing carbon storage and sinks can effectively reduce atmospheric CO_2 concentrations, mitigate greenhouse effects, and regulate global climate change (Goheer et al., 2023; Berc, 2004; Critchley et al., 2023). Terrestrial ecosystems are crucial in storing carbon, encompassing above and below-ground biomass, soil organic matter, and dead organic matter pools. Forests store carbon in tree biomass, soil organic matter, and dead organic matter (e.g., fallen leaves, decaying plant material). Forests and shrublands can absorb and store large amounts of CO_2 through photosynthesis, where plants convert CO_2 into glucose and oxygen. While natural conditions allow terrestrial ecosystems to act as carbon sinks, LULC changes can also turn them into carbon sources (Zhao et al., 2013; S. Li et al., 2022; M. Zhao et al., 2019).

The change in LULC is a major environmental challenge globally, affecting ecological processes worldwide (Klimanova et al., 2017). Change in LULC is a complex and dynamic processes that affect ecosystem services and carbon storage (Shao, 2005; Meshesha et al., 2014), and LULC changes caused by anthropogenic activities impact terrestrial carbon storage (Zaehle et al., 2007). For instance, carbon stock dynamics have significant implications for climate change management. Changes in land cover, such as forest deforestation and degradation, have a direct impact on ecosystem carbon stocks. Forests mitigate climate change by absorbing carbon dioxide from the lower atmosphere. Forest biomass and soils mitigate climate change via carbon sink and storage (Solomon et al., 2018; Rice, 2010; Tadesse, 2023). However, LULC change also aggravates socioeconomic & environmental problems by altering land management practices at the landscape scale, disrupting biodiversity and hydrological cycles, reducing carbon sequestration potential, and reducing groundwater (Lambin et al., 2003; Lambin & Meyfroidt, 2011). In addition, it also affects evapotranspiration, infiltration, climate patterns, socioeconomic dynamics, and natural spectacles at local level & worldwide scales (Chakilu & Moges, 2017; Akpoti et al., 2016).

The change in LULC challenges the sustainable use of natural resources such as provision of water, forests, woodlands, & grasslands (Arshad et al., 2022; Lira et al., 2012; Gebrehiwot et al., 2014). The LULC changes can lead to increased ecosystem services provisions while diminishing other services that support human needs, indicating environmental degradation. Alterations or changes in LULC directly impact biological diversity, resulting in ecosystem service changes and affecting biological systems supporting basic human needs. It also influences the vulnerability of people and their homes to climatic problems, economic crisis, or socio-political disruptions (Najmuddin et al., 2022).

Both human activities and climate change can contribute to LULC changes. Human actions, including urban development and agriculture practices, can cause the permanent loss of natural and working lands, resulting in localized changes in weather forms, temperature, & precipitation (Feranec & Soukup, 2012). Changes in LULC are mostly influenced by population growth (Lambin et al., 2003), economic growth, and physical factors, including topography, slope conditions, soil type, and climate. These changes also significantly alter Earth's climate by altering circulation patterns, surface albedo, and atmospheric carbon dioxide levels (Feranec & Soukup, 2012; Ge et al., 2022). Global economic and population growth, as well as globalization, have altered the LULC in many developing countries due to competing demands and limited resources, which severely disrupt various ecosystem services and functions (Kolb et al., 2013).

Assessing environmental services is crucial to understand the benefits of enhancing human well-being and ensuring sustainable ecosystem management (Costanza et al., 2014).

Ecosystem service valuations are being shown to be useful in extending biodiversity conservation outside of protected areas (Hauck et al., 2013). The valuation of ecosystem services has experienced recent growth in both research and policy-making (Li et al., 2010; Hu et al., 2008; Costanza et al., 2014), adhering to the introduction of the ESV model by Costanza et al. (1997) and MEA (2005).

Ecosystem service valuation is expected to demonstrate the social significance of ecosystem services and can assist resource managers in dealing with the consequences of market failures by calculating the societal costs in terms of decreased economic benefits. However, the ecosystem service concept has faced criticism because it is anthropocentric and exploitative, conflicts with biodiversity conservation, encourages the commercialization of nature, and is vague (Schröter et al., 2014). It has also been criticized for relying heavily on economic metaphors, viewing ecosystems as natural capital reserves (Muradian & Gómez-Baggethun, 2021), and for being associated with the commoditization of nature (Costanza, 2006). Despite this criticism, the ecosystem service framework has the genuine intention of environmental protection (Muradian & Gómez-Baggethun, 2021). It emphasizes the interconnectedness between economic and ecological systems and highlights nature's fundamental role in supporting both the economy and human life (Gómez-Baggethun et al., 2010).

Although the intrinsic value of nature cannot be replaced by the value of environmental goods and services (Costanza, 2006), the need for survival often takes precedence over the intrinsic value of nature in developing countries. In such cases, the use of environmental services as an approach to obtain societal support for ecosystem protection is widespread (Braat & de Groot, 2012). To address criticisms of the ecosystem service framework, a study could incorporate proper valuation methods to balance anthropocentric and intrinsic values of nature by examining the ESV by defining specific services and tailoring the research to context-specific needs to overcome the vagueness of the framework and offer a more holistic understanding the relations between ecosystems, economy, and society.

The rapid increase in deforestation, as well as poor practices of managing farmlands accelerating land degradation & soil erosion in the Ethiopian highlands (Yesuf et al., 2015), is principally common where high populations exist and their livelihoods directly depend on the exploitation of natural resources. Such fast rates of vegetation conversion, unsustainable agricultural land use, and severe soil erosion have resulted from LULCC and land degradation in the Ethiopian highland. Because of population pressures, economic factors, and policy issues, settlements, farmland, and degraded lands have been expanding while grasslands and forest areas have been diminishing largely (Yesuf et al., 2015; Gebrelibanos & Assen, 2015; Alemu et al., 2015). Moreover, LULCC is associated with deforestation, biodiversity loss, and land degradation in Ethiopia (Maitima et al., 2009; Gifawesen, 2019). Thus, LULCC is a serious problem in changing the environment.

The Basin is indeed a critical area for environmental sustainability, with its diverse ecosystems contributing significantly to carbon storage and a range of vital ecosystem services. These services, including water purification, flood control, climate regulation, and wildlife habitat, are crucial for the local communities that depend on the basin for agriculture and water supply. However, the challenges posed by land degradation, depletion of water resources, population growth, and urbanization are substantial, as highlighted by previous studies (Daba & You, 2022; Edossa et al., 2010). The alteration to agricultural land along the basin has led to considerable LULC changes. This has resulted in the change of natural vegetation to cultivated areas, which has negative consequences like biodiversity loss, deforestation, & drops in wetlands. These transformations also affect sustainable services provided by the ecosystem. Understanding the socio-economic drivers behind land-use change is essential for implementing effective, sustainable land-use policies. In the Upper Awash River Basin, local communities are often dependent on agriculture and natural resources for their livelihoods. The basin LULC may be caused by the growth of population, agricultural expansion, poverty, and the need for income generation. Integrating socio-economic data with ecological research can help build more effective policy recommendations. It’s essential to consider how to balance the needs of local communities with the need to preserve ecosystem services.

The Upper Awash River Basin is a diverse landscape encompassing multiple ecosystems such as forests, wetlands, shrublands, croplands, and urban areas. Each of these ecosystems plays a distinct role in carbon cycling and provides various ecosystem services. However, much of the current research focuses primarily on forest ecosystems, which, while crucial, represent only a portion of the broader ecological picture. Given these changes, a comprehensive approach to assess carbon stock dynamics and ecosystem services in the basin is key for ensuring land resource management & understanding the contributions of each land-use to the carbon cycle, ESV, and how LULC changes affect these processes. Given the vast spatial scale of the Upper Awash River Basin, traditional ground-based monitoring can be resource-intensive and limited in scope. However, Remote Sensing and Geographic Information Systems offer powerful tools to monitor land-use changes at the landscape scale. These technologies enable researchers to analyze spatial patterns of vegetation cover, land degradation, urban expansion, and agricultural intensification over large areas.

Expanding research to cover a broader range of ecosystems, employing advanced technologies for monitoring, incorporating socio-economic perspectives, and valuing ecosystem services are all essential steps in addressing the knowledge and research gap around LULC changes in the basin. The study would aid in identifying key areas for conservation, enhancing environmental resilience, contributing to the sustainability of water resources management, and maintaining biodiversity. This study would not only support ongoing conservation efforts but also help safeguard the long-term ability of the basin’s ecosystems to continue providing sustainable services to local communities. This research is also essential for developing strategies that balance development with environmental protection, ensuring that the basin remains a sustainable resource for future generations.

1.2. Statement of the Problem

The Awash River Basin, due to its strategic location and access to essential resources, plays a critical role in supporting various sectors, including agriculture, industry, and domestic use (Taddese et al., 2004). However, its ecological sustainability is increasingly threatened by both human activities and environmental pressures. The region's rapid population growth, combined with agricultural expansion and urbanization, has caused significant degradation of natural resources and ecosystems. Land degradation, driven by deforestation, soil erosion, and overgrazing, threatens the basin’s long-term sustainability (Nanesa, 2021; Assegide et al., 2022). The forest area in the Awash basin has drastically decreased from 7.31% (695.11 km²) in 1984 to just 0.82% (78.25 km²) in 2019, indicating a loss of approximately 88.7% of forest coverage over this period (Daba et al., 2020). This trend is expected to continue, with projections suggesting further reductions in forest area due to agricultural expansion and urbanization. The population within the Awash River basin is estimated at over 18 million, with a density exceeding 6,452 persons/km² (Duguma et al., 2021). This rapid growth has intensified pressure on land and water resources, contributing to deforestation and water quality degradation. Moreover, the increasing water demand, exacerbated by climate variability, further strains the available resources. The impacts of these human-induced factors include declining water quality and availability, which affect not only the local community but also the industries and agricultural activities that depend on the river. The total area covered by water bodies has also diminished significantly, dropping from 0.38% (36.49 km²) in 1984 to 0.23% (21.51 km²) in 2000, and further to 0.18% (17.51 km²) by 2019 (Duguma et al., 2021). This decline in water bodies correlates with increased pollution from agricultural runoff and urban waste. Climate change and erratic rainfall patterns add another layer of complexity, making water management and conservation efforts even more critical.

The Awash River Basin is experiencing environmental challenges due to a combination of human activities. These activities, such as irrigation, industrial development, and residential expansion, are contributing to land degradation, natural resources depletion, & the disruption of environmental balance (Hailemariam, 1999; Mengistu, 2008). The basin's economic utilization for irrigation, industrial development, and settlement expansion likely leads to alterations in the natural carbon cycles and the overall ecosystem. The expansion of agriculture practices in the area resulted in deforestation, reducing carbon sequestration potential and affecting local climate patterns. The population pressure and their demand for resources intensify the strain on the environment, resulting in land degradation and reduced services by the ecosystem, namely water refinement, flood control, & biodiversity.

Studies by Daba & You (2022) and Edossa et al. (2010) highlight key environmental challenges in the basin, including land degradation, water resource depletion, rapid population growth, and urbanization. These issues are often driven by unsustainable agricultural practices and settlement expansion, which significantly harm the ecosystem, making it more difficult to maintain both the land and water resources necessary for the region's sustainability. The expansion of large-scale irrigated agriculture along the basin has led to LULC changes, including converting natural vegetation to cultivated land, resulting in a loss of biodiversity, deforestation, and a reduction in wetland, fuel wood, and construction materials. While the Upper Awash River Basin is vital for carbon storage and ecosystem services, it faces challenges from climate change, governance issues, and land use changes that require immediate attention for sustainable management. The conversion of natural vegetation to cultivated land has led to biodiversity loss and diminished ecosystem services.

This study addresses a significant research gap by exploring how LULC changes impact carbon stocks & ecosystem services in the basin, an underexplored topic, particularly at a landscape level. While previous studies have focused on isolated sites or forest ecosystems, this research takes a broader approach by analyzing the entire basin, including both forested and non-forested land uses. By integrating ecological and socio-economic factors, the study also offers a comprehensive understanding of how LULC changes affect carbon storage and ecosystem services across the region. This will provide a more comprehensive understanding of how LULC changes affect carbon storage and ecosystem services at a broader scale, considering both forest and non-forest land uses. By leveraging satellite imagery, GIS tools, the InVEST model, and others, the study helps track and map spatial and temporal patterns of LULC changes across the basin. This allows for precise quantification of the degree of LULC changes over time, and correlates these with shifts in carbon stocks and ecosystem services.

1.3. Significance of the Study

The impacts of LULC changes on carbon storage and ecosystem function have received much attention recently (Leh et al., 2016; Newbold et al., 2015; Chen et al., 2017). To gain a better understanding of how carbon stocks change over time, it's essential to assess their dynamics in areas experiencing rapid land use and land cover shifts. This information is key to developing effective land management policies aimed at maintaining carbon storage and supporting ecosystem health (Muleta, 2017; Meshesha et al., 2014).

Modelling LULC change is crucial for effective long-term resource management, climate change mitigation, & understanding hydrological processes, particularly at the basin scale for water resource development and managing extreme events (Kindu et al., 2016; Wang et al., 2020; Wang et al., 2021; Tao et al., 2023). The role of RS in providing timely and precise data across large areas is crucial to monitor LULC changes. These techniques help track the spatiotemporal patterns of carbon storage on a broad scale. The InVEST model, which uses remote sensing data, is particularly valuable for analyzing ecosystem services like carbon storage dynamics. The model estimates the amount of carbon stored in a landscape, considering different carbon pools based on LULC data. This integration of technologies enables a thorough examination of how the changes affect carbon dynamics, thereby assisting in informed conservation efforts & better land management in a sustainable manner (Zhu et al., 2022; Bobrinskaya, 2012; Ullah et al., 2019). The model aids stakeholders such as governments, NGOs, and businesses in making informed decisions about environmental services & conservation at the landscape for the sink & storage of carbon (Maanan et al., 2019; Li et al., 2023).

Field measurements are the most reliable method for estimating carbon stocks in terrestrial ecosystems, but they become less efficient and more expensive when applied to large areas. To address this issue, models could be used to combine field measurements and remote sensing data in ways that make it easier to estimate changes in carbon reserve at landscape (Malik et al., 2022; Havemann, 2009; Goetz et al., 2009). Remote sensing is widely used for vegetation mapping and monitoring, allowing detailed analysis of vegetation cover, estimating biophysical properties, and monitoring shifts in coverage of vegetation over time (Almalki et al., 2022; Lustenhouwer, 2009; Xie et al., 2008). Different vegetation index namely SAVI, NDVI, & EVI are regularly used in RS to estimate carbon stocks on a large scale, making them efficient and less labour-intensive than traditional field measurements (Malik et al., 2022). The correlation between landscape carbon estimation and vegetation indices is vital in understanding ecosystem health, carbon stock changes, afforestation programs, as well as conservation strategies. It helps prioritize conservation efforts, identify high carbon stock potential, and assess land-use changes on carbon dynamics. This correlation validates remote sensing techniques for estimating carbon stocks and improves carbon accounting models.

Ecosystem service valuations are useful in extending biodiversity conservation outside of protected areas (Hauck et al., 2013). The ESV has experienced recent growth in both research study & in making policy decisions (Costanza et al., 1997; Y. Li et al., 2010; Liu et al., 2010) adhering to the introduction of the ESV model by (Costanza et al., 2014) and (MEA, 2005). Assessing ESV is crucial to understanding its benefits in enhancing the livelihood of the local community and ensuring sustainable ecosystem management (Costanza et al., 2014). Also, understanding the effects of land shifts on ESV & carbon stock dynamics is critical for raising public awareness, guiding policy decisions, and facilitating climate change mitigation and adaptation. Thus, this study investigated the changes in carbon stocks & services provided by the ecosystem associated with LULC change over thirty years (1993-2023). This research aims to advance our understanding of ecosystem carbon stock estimation and inform strategies for preservation & mitigate change in the climate within the Upper Awash River Basin.

1.4. OBJECTIVE

1.4.1. General Objective

The overall aim of the research was to evaluate the effects of LULC changes on ecosystem services in the Upper Awash River Basin.

1.4.2. Specific Objectives

- To evaluate the LULC change pattern from 1993 to 2023;
- To explore the influence of LULC shifts over thirty years on the temporal & spatial variations in carbon stocks;
- To quantify the impacts of LULC shifts on the ESV from 1993 to 2023, along with the monetary value loss; and
- To estimate the basin's overall carbon stock by evaluating the relationship between vegetation indices and landscape carbon estimates.

1.5. RESEARCH QUESTIONS

1. What are the trends, patterns and drivers of LULC changes from 1993 to 2023?
2. How do LULC changes affect carbon stock over thirty years?

3. What is the monetary value of each ecosystem service in different land use types, and how do LULC changes impact ESV in the basin?
4. What are the relationships between vegetation indices and landscape carbon estimates?

1.6. CONCEPTUAL FRAMEWORK

This research study maps and quantifies services provided by terrestrial ecosystems and carbon stock dynamics, while also examining how this change is due to LULC changes. It also engages with theories of LULC change, which suggest that shifts in land use are caused by a combination of socio-economic & ecological features. The research links these broader theories by showing how human activities, including agricultural practices and urban development, influence land-cover types, which in turn impact carbon stored in the terrestrial ecosystem & ecosystem services provided. It emphasizes integrating remote sensing data with field data to understand human impacts on the environment and how these impacts interact with economic activities. This combination of remote sensing and field data provides a comprehensive approach to monitoring environmental changes over time.

The InVEST model, used alongside ArcGIS, serves as a powerful tool to estimate carbon stocks and evaluate ecosystem services across different landscapes. This approach is particularly useful for conservation and land management, helping stakeholders make informed decisions about natural resource management. The study uses LULC classifications and carbon pool data to inform the InVEST model's carbon stock estimations in both forested and non-forested ecosystems. By comparing vegetation indices from remote sensing with field data, the research aims to accurately estimate the carbon stock within the Upper Awash River Basin. This integration of remote sensing and field data strengthens the reliability of carbon stock estimates across various ecosystems and provides a better understanding of ecological dynamics. The methodology also supports climate change mitigation efforts by quantifying the role of the ecosystem in carbon storage. To understand the economic benefits of the Upper Awash River Basin's ecosystem services, the study estimates ecosystem service values (ESV) using global average values. By estimating the economic value of terrestrial ecosystem ESV, the study integrates socio-economic dimensions into the broader theory of LULC change, emphasizing the status of incorporating both ecological and economic factors into land management strategies.

Remote sensing data helps to track changes over time, further supports these theories by enabling the detection of spatial and temporal shifts in land cover, and provides insights into the dynamic processes driving land-use transformations. This process includes quantifying the various services ecosystems provide, namely provision, regulation, supportive & cultural, and expressing them in monetary terms. The different land-use systems and biophysical components influence ecosystem valuation. Having accurate ESV data helps decision-makers create effective land-use plans and manage ecosystems, which is essential for preserving natural resources and promoting public health. This data also helps optimize investments from donors, businesses, and producers.

This study not only applies ecological and economic theories but also contributes to them by offering an integrated, data-driven approach to understand the relationships between LULC, terrestrial ecosystem services, & carbon stocks while providing practical insights for decision-makers in land management and conservation.

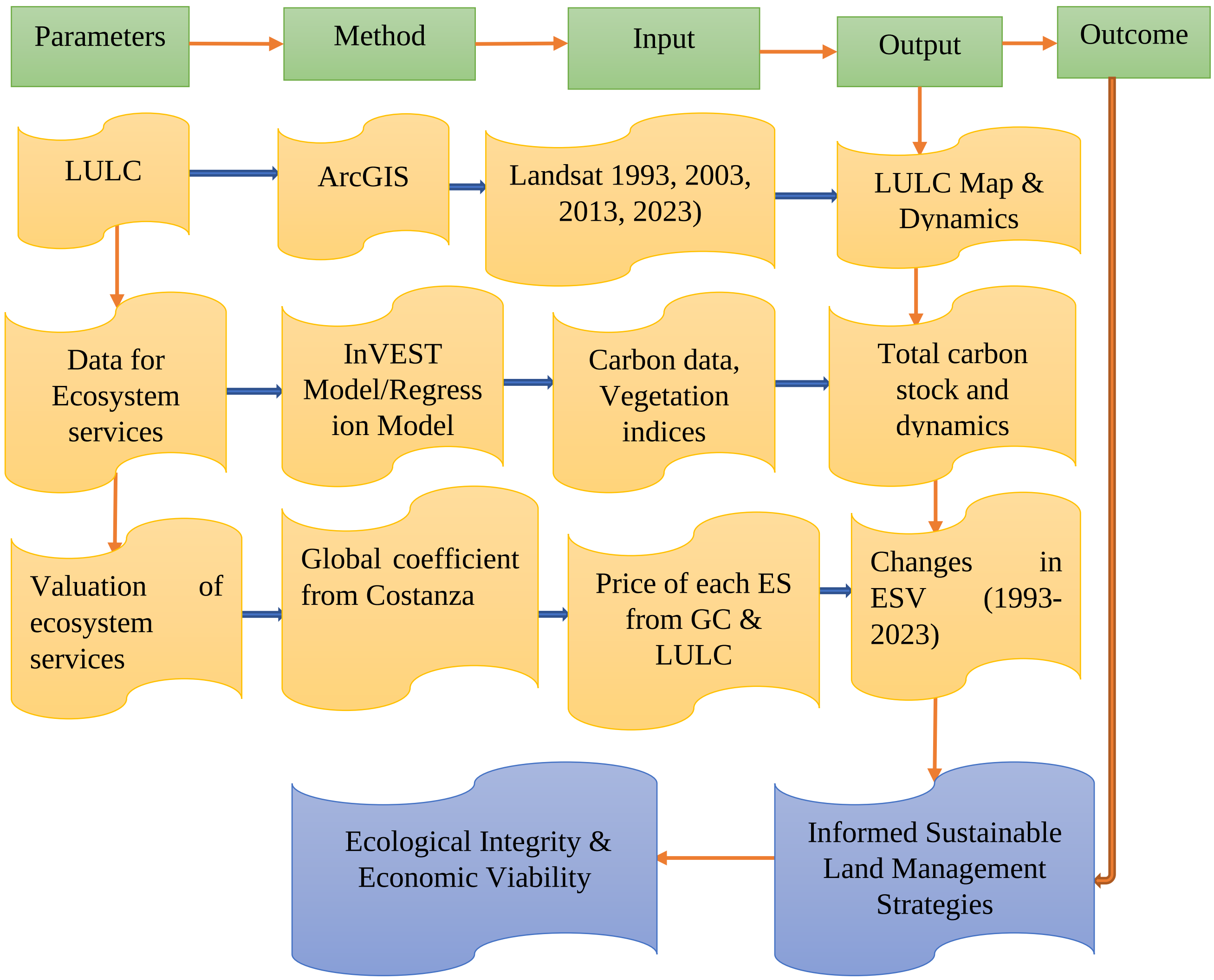


Figure 1. Conceptual framework

1.7. OUTLINE OF THE DISSERTATION

There are six chapters in this dissertation. Chapter One introduces the research topic and provides background information and sets the stage for the dissertation by outlining the research problem, aims, objectives, and significance. Existing literatures relevant to the research topic were reviewed in Chapter 2. This chapter also identifies gaps in the current knowledge that the dissertation aims to address, providing context for the study. In Chapter 3, the study area was introduced, evaluation of LULC dynamics, carbon stock estimation for each LULC, ecosystem service value estimation, and vegetation indices mapping and extraction were described. The results are organized in Chapter 4. This chapter presented the findings on LULC change and its drivers, ESV, carbon stock dynamics, and carbon stock estimation using vegetation indices. A discussion of the findings presented and discussed in Chapter 5, provides a strong explanation of the findings. Chapter 6 covers the conclusion and recommendations.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. LULC CHANGES AND ECOSYSTEM SERVICES

2.1.1. LULC changes, drivers, and their impact

2..1.1.1 LULC Concepts

The term land use describes the human activities and management practices that occur on a specific piece of land. This encompasses agriculture, forestry, urban development, and recreational activities. Land use reflects the socio-economic functions of the land and how humans utilize it. On the other hand, land cover states the physical & biological material covering the surfaces of the earth. It includes various types such as forests, wetlands, grasslands, and urban areas. Essentially, land cover represents the observable state of land, indicating what is physically present, like vegetation or constructed structures. Di Gregorio, A., and Jansen, (2000), define land cover as the biological cover on the surfaces of the ground, including natural features and man-made structures. This encompasses how land is utilized for various purposes, such as industrial zones, residential areas, and agricultural practices. From this, land cover reflects the solid state of the terrestrial, whereas land practice or use captures the human interactions with that land. Understanding the dissimilarity between land cover & land use plays a crucial role in many fields, including environmental monitoring, urban development, and resource administration. The interplay between LULC is vital for assessing environmental changes and planning for sustainable development (Aydinoglu et al., 2010). By recognizing that each parcel of land is unique in its cover type and usage, stakeholders can make better decisions that balance ecological integrity for human needs.

The concepts of LULC are closely linked; shifts in one often lead to alterations in the other. For instance, converting forested areas into agricultural land (land use change) results in a corresponding alteration in land cover from forestland to cropland. Conversely, natural events such as wildfires can alter land cover without immediate changes in land use (Somantri & Nandi, 2018). LULC change has occurred due to the transformation of the Earth's surface due to human action & natural methods (Lin et al., 2018). This includes transforming natural landscapes into urban areas, agricultural land, or other uses, significantly impacting ecosystem services, biodiversity, and climate regulation (Lin et al., 2018). Human-driven LULC changes like urbanization, agriculture, and deforestation typically increase pressure on natural ecosystems and lead to ecosystem challenges, such as poor climate regulation and substantial biodiversity loss. Monitoring LULC change is essential for understanding how these shifts affect ecological sustainability and creating strategies to mitigate negative impacts.

Since the late 1960s, the rapid development of vegetation mapping has led to increased studies of LULC change worldwide. A precise assessment of the amount & health of the global forest, grassland, and agricultural resources has become an important priority. A region's LULC pattern results from natural and socioeconomic features & their utilization by the local communities in a given area over a specific period. Information on LULC change assists in monitoring the dynamics of LULC resulting from the changing demands of the increasing population (Ahadnejad et al., 2009).

LULC change without appropriate management practices has been recognized as a main reason leads to land degradation, with significant impacts on the services provided by terrestrial ecosystems & climate change, hence on human livelihoods. Thus, accurate LULCC data and maps at different spatial scales are significant for regular monitoring of existing ecosystems, proper planning on the management of natural resources, & promotion of sustainable regional growth (Astou Sambou et al., 2023). LULC changes are critical environmental phenomena that reflect the dynamic interactions among human activities & natural ecosystems. It generally refers to altering Earth's landscapes brought about by either natural or human-caused events. This encompasses a variety of changes, such as converting forests into urban areas, agricultural land, or other, which can significantly affect ecosystem services, biodiversity, and climate regulation.

2.1.1.2. LULC change drivers

The key drivers of LULC change include population growth, agricultural expansions, economic development, investment, policy changes and social factors, climate changes, and environmental factors (Bufebo & Elias, 2021; Niu et al., 2019; Allan et al., 2022). Shifts in land cover are significant indicators of global environmental challenges, mostly determined by the interventions made by human beings. These changes have deep consequences for biodiversity, climate, and services provided by ecosystem (Zhang & Liang, 2018; Lin et al., 2018). The change in land-use modify its cover due to human intrusions, such as cultivation, settlement, transportation, infrastructure, manufacture, recreation, mining, and fishing (Allan et al., 2022; Bufebo & Elias, 2021). LULC changes are driven by natural factors and anthropogenic activities (Bennett & Saunders, 2010), causing the alteration of ecological processes and the loss of native biodiversity across different ecosystems (Fasika et al., 2019; Msofe et al., 2020). LULC is continually altering in response to the shifts in interaction between drivers of change and immediate causes (Munthali et al., 2020; Yesuph & Dagnew, 2019; Fasika et al., 2019).

The growth of population is a substantial cause of LULC change in the country, with studies indicating it influences land use decisions in 95% of cases. As the population pressure rises, there is a greater need for food, housing, & infrastructure, leading to the conversion of forestland to agricultural and built-up area (Berihun et al., 2019; Bekele et al., 2019). Fuelwood collection is another critical factor driving LULC changes. With a substantial share of the population relying on wood for cooking and heating, this practice leads to forest degradation & deforestation, impacting the overall environmental services (Bekele et al., 2019; Mariye et al., 2022).

Research focusing on southwest Ethiopia, particularly Jimma, shows a marked rise in urban areas over the last 60 years. Urban expansion has led to a decline in vegetation coverage and croplands. This trend is evident in cities like Jimma, where built-up areas expanded significantly over the past decades while vegetation decreased substantially (Dessu et al., 2020). The primary drivers identified for these LULC changes include population growth, urbanization, expansion of farmland, and fuel wood collection. Local communities have recognized these factors as significant contributors to the transformation of land use patterns (Mariye et al., 2022). The study also notes a correlation between LULC changes and local climate variations. There has been a significant increase in temperature over recent decades alongside a decrease in annual rainfall. This shift is attributed to rapid urbanization and the resultant decline in green spaces, which can exacerbate local climate issues (Dessu et al., 2020).

The LULC change is a critical area of study that highlights the intricate connection between interventions by humans & the natural state. Understanding these changes is vital for fostering sustainable development and preserving ecological integrity. The trends observed in Ethiopia underscore the need for proactive measures to manage land resources sustainably, while addressing the problems caused by rapid urbanization & environmental transformation.

2.1.1.3. Impacts of LULC changes

The changes are driven by various factors and have adverse effects on the environment, biodiversity, & livelihoods of local communities. For instance, forests and wetlands conversion into cropland or urban areas often results in habitat loss, biodiversity decline, and increased soil erosion (Bufebo & Elias, 2021), altering the carbon storage capacities of ecosystems (Esengulova et al., 2024), influencing land use decisions (Hailu et al., 2020), disrupting traditional livelihoods and ecosystems (Hailu et al., 2020). Land cover types such as forests are vital for carbon sequestration. Land cover changes that involve deforestation or degradation reduce this capacity, contributing to higher atmospheric CO_2 levels. For instance, the alteration of forestland to cropland releases stored carbon dioxide, a major driver of global warming. Agricultural practices can also lead to methane and nitrous oxide emissions, particularly from livestock and fertilization processes (Bununu et al., 2023; Jia et al., 2022).

Recent findings on LULC changes in Ethiopia highlight significant transformations driven by urbanization, agricultural expansion, government policy, and environmental factors. For instance, the conversion of forests for new farmlands, settlements, charcoal production, and timber leads to reduced forest cover, with remnants found only in inaccessible areas (Dibaba et al., 2020). These changes have critical implications for local ecosystems and the climate. For instance, agricultural expansion in Ethiopia has significantly altered LULC patterns, primarily determined by the demand to accommodate population pressure & improve food security. This transformation has profound implications for the country's environment, economy, and social structures. Urban expansion significantly impacts agricultural land by converting it into built-up areas for housing, infrastructure, and other non-agricultural uses. This expansion leads to a reduction in the area available for agriculture, affecting peri-urban farmers and increasing their vulnerability (Ayele & Tarekegn, 2020).

2.1.1.4. Land use planning policies role

The LULC changes in Ethiopia are significantly influenced by government policies, which impact agricultural practices, urban development, and environmental conservation. These changes often result from policies aimed at raising the productivity of land & food security, but can lead to ecological issues such as the loss of habitat & soil fertility (Dejenie & Kakiso, 2023). Government policy acting as a vital role in determining LULC changes in Ethiopia. Policies influence agricultural practices, urban development, and environmental conservation, directly impacting the sustainability of land resources (Terfassa Fida et al., 2024). The current land tenure system in Ethiopia emphasizes public ownership of rural lands with restrictions on land transfers. This has resulted in tenure insecurity among farmers, affecting their ability to invest in sustainable practices. Policies aimed at increasing agricultural productivity have led to significant land conversion from natural ecosystems to farmland. While these policies are designed to enhance food security, they often overlook the ecological consequences, resulting in habitat loss and soil degradation (Teka et al., 2013). The effectiveness of environmental policies in Ethiopia has been inconsistent. Although there are frameworks intended to protect forests and manage land sustainably, poor implementation and enforcement have allowed deforestation and land degradation to persist. Although frameworks exist for forest protection and sustainable land management, poor implementation allows deforestation and degradation to persist. For instance, many regions experience high rates of erosion due to inadequate management practices encouraged by agricultural policies (Hussein, 2023). Government-led resettlement initiatives aim to alleviate poverty by relocating communities to less populated areas for agricultural development. However, these programs can lead to increased pressure on local ecosystems as new settlers convert forests and grasslands into farmland without adequate planning or support for sustainable practices (Terfassa Fida et al., 2024).

Understanding the distinction between LULC is vital for the management of the environment. By incorporating both ideas into planning procedures, communities can preserve natural ecosystems and promote sustainable development. By examining LULC change patterns, stakeholders can more effectively plan for sustainable development while reducing detrimental effects on ecosystems. In light of continuous global change, integrating these facts into the planning of land use for maintaining biodiversity and improving ecosystem services.

2.1.2. Role of GIS and RS in LULC changes

Geographic Information Systems (GIS) and Remote Sensing (RS) techniques have become essential tools for studying historical changes in LULC across the globe. These technologies facilitate the monitoring and analysis of LULC changes over time, providing critical insights into environmental dynamics, urbanization, and land management (Aboelnour & Engel, 2018; Rane et al., 2023). GIS and RS enable researchers to detect and quantify shifts in LULC. They facilitate the analysis of various factors influencing LULC, such as urban expansion, agricultural development, and deforestation. Remote sensing utilizes satellite and aerial imagery to capture the reflectance of the Earth. This allows for identifying and characterizing various land cover types, such as forestland, urban areas, agricultural land, & water bodies (Kareem Sameer, 2023; Mashala et al., 2023).

The combination of RS data with GIS enhances spatial investigation capabilities of the study. This combination permits for detailed examination of LULC deviations with other geographic factors, such as topography and climate. New web-based platforms and open data initiatives are making remote sensing data more accessible, enabling broader applications in monitoring LULC changes across different regions (Mashala et al., 2023). RS and GIS are also used to understand the impacts of LULC deviations on the terrestrial ecosystems. For instance, it can help to monitor deviations in vegetation cover and detect changes in carbon storage, a crucial factor in climate change mitigation. Detecting LULC change involves comparing LULC maps derived from different periods using RS data obtained from satellite, airborne, or ground-based sensors that capture information on the Earth's surface's spectral, temporal, & spatial characteristics. Spectral information reflects the reflectance or emission of energy by different land cover types in various wavelength bands, while temporal information reflects seasonal and yearly variations in LULC patterns. Spatial information reflects the location and extent of LULC features, which are represented as pixels in digital images (Shrestha, 1970; Hassan, 2014; Kumar, 2018; Kumar et al., 2015).

Remote sensing is the main source for several kinds of thematic data critical to GIS analyses, including data on LULC characteristics. Aerial and Landsat satellite images are also frequently used to evaluate land cover distribution and to update existing geospatial features. With the introduction of RS & image processing software, the importance of RS in GIS has expanded significantly (Merchant et al., 2009). Accelerated usage of RS data and techniques has made the geospatial process faster and more powerful, although the increased complexity also creates increased possibilities for error (Rwanga & Ndambuki, 2017; Krishna et al., 2013).

GIS and RS enable the mapping and quantification of various LULC types, such as cultivated land, forest cover, grazing land, and urban areas. These technologies allow for multi-temporal data analysis, which is essential for detecting changes across different periods. The integration of historical satellite imagery with current data helps researchers understand trends and predict future changes (Venukumar, 2022; Abebe et al., 2022). While GIS and RS provide powerful tools for analyzing LULC changes, challenges remain regarding the integration of local knowledge with scientific data. Effective LULC studies often require a combination of remote sensing techniques with ground-truthing methods to ensure accuracy and relevance at local levels (Abebe et al., 2022; Venukumar, 2022).

In remote sensing, satellite imagery and aerial photos are used to detect & map LULC types, such as forests, urban areas, agriculture, water bodies, etc. Changes over time can be tracked through the comparison of images from different periods. The LULC change analysis can effectively be conducted using Landsat sensor data, specifically the MSS and TM imagery, through various image cataloguing methods. This approach has been extensively documented in the literature, including work by (Vittek et al., 2013; Zaidi et al., 2017; Kovalskyy & Roy, 2013). Since its inception in 1972, the Landsat satellite program has provided consistent, high-resolution multispectral imagery of the Earth's land surfaces. This program has significantly contributed to our understanding of LULC changes over time, making it a valuable resource for scientific research and environmental monitoring (Sudhakar & Rao, 2010) and their evolution is further marked by the launch of Landsat-7 & Landsat-8 by the United States in 1999.

Geographic information systems & RS are effective instruments utilized in many domains, including environmental monitoring, urban planning, and natural resource management (Parra, 2022). However, they often require complementation with other techniques like surveys & participatory mapping to provide a full study of geographical phenomena (Sakshi et al., 2023; Parra, 2022). For instance, remote sensing offers quick, large-scale coverage and can access remote areas, but it misses small-scale changes and requires validation. GIS integrates diverse datasets to support decision-making, though its effectiveness depends on input quality and requires technical expertise. Field surveys provide detailed ground-level information but can be time-consuming and costly over large areas. Participatory mapping engages communities and captures local knowledge, though it can be subjective based on participants' views and requires active community involvement (Sakshi et al., 2023; Parra, 2022). While GIS and RS are powerful tools, they have limitations and are susceptible to errors. Some of these challenges include integration challenges, complexity, data analysis issues, data presentation, generalization, and data loss. These errors can significantly impact the precision & consistency of the work (Lunetta et al., 1991). Minimizing errors in GIS data is crucial for ensuring the accuracy and reliability of spatial analyses (ESRI, 2011). Some best practices to help reduce errors and enhance the quality of spatial analyses are data validation (geometry and attribute) and verification (visual and metadata review) methods.

2.1.3. LULC change analysis

Image classification

Image classification helps to produce land use and land cover maps. It is the process of assigning pixels in a digital image to specific classes or themes based on their spectral characteristics. Image classification helps in examining LULC changes, particularly through remote sensing techniques. This process involves categorizing pixels in satellite images to produce detailed maps that reflect the various types of LULC changes. It is a fundamental technique in digital image analysis and remote sensing for extracting information from images (Vision, 1993; Bogoliubova & Tymków, 2014; Di Gregorio, 2016). Selecting cloud-free images is a crucial step in remote sensing, but it faces significant challenges, particularly in regions with frequent cloud cover or during specific seasons. A combination of strategies, such as cloud masking, atmospheric correction, and data fusion, can help to reduce the atmospheric effects on the value of remote sensing data (Anzalone et al., 2024; Wu et al., 2022). The combination of these strategies allows researchers to generate high-quality composite images that better represent land surface changes over time. The approach is particularly valuable in areas where persistent cloud cover hampers traditional remote sensing techniques.

According to Ji & Jensen, (1996) and Al-doski et al., (2013), digital image classification is assigning or sorting pixels into a finite number of individual classes, or categories of data, based on their data file values. Usually, each pixel is treated as an individual unit composed of values in several spectral bands. By comparing pixels to one another and pixels of known identity, it is possible to assemble groups of similar pixels into classes that match the informational categories of interest to users of remotely sensed data. High-quality satellite imagery, such as Landsat data, is essential for effective image classification. The accuracy of the classification is heavily dependent on the quality and resolution of the input data. Digital image classification is divided into two types: supervised and unsupervised classification.

The presence of mixed pixels in heterogeneous landscapes significantly impacts the accuracy of digital image classification. Mixed pixels occur when a single pixel captures data from multiple land-cover types, meaning it doesn't represent one specific class but rather a combination of several (Rana et al., 2025; M. Liu et al., 2020). Mixed pixels can lead to spectral overlap between different land cover types. For example, if a pixel contains data from both forest and agricultural fields, its spectral signature may not match either category alone (M. Liu et al., 2020). Traditional classification algorithms struggle with mixed pixels because they often rely on clear spectral signatures for each class. In heterogeneous environments, these signatures can be ambiguous or variable due to environmental factors like lighting conditions or soil background. The problem of mixed pixels is exacerbated by lower spatial resolution images since each pixel covers more area and is more likely to include multiple land cover types (M. Liu et al., 2020). High-resolution images reduce this issue but introduce other challenges like increased spectral variation within classes (Moran, 2011). This issue is particularly pronounced in diverse landscapes, such as areas containing forests, plantations, and agricultural fields.

Unsupervised classification

Unsupervised classification is an approach that uses statistical clustering techniques to combine pixels into groups (classes) based on the degree of similarity of their brightness value in each spectral band. Using maps and field-based knowledge, the analyst then combines spectral classes into real land cover types. The analyst should understand the spectral characteristics of the terrain in the area of interest well enough to properly label certain clusters into a specific information class (land cover type). Many spectral classes can be assigned to a few land cover types (Ji & Jensen, 1996).

Supervised classification

This method relies on training samples where the analyst selects specific areas known to represent certain land cover types. The spectral signatures from these samples are then used to classify the entire image. This approach is highly effective when high-quality training data is available. Supervised classification involves grouping pixels based on known site identified, using fieldwork, aerial photography, maps, and expert experience to categorize LULC types (Ji & Jensen, 1996). By employing various classification techniques, whether supervised, unsupervised, or hybrid, analysts can effectively interpret complex satellite data and produce meaningful insights into land cover dynamics. The choice of method is often based on the specific requirements of the examination & the quality of available data.

In remote or inaccessible areas, collecting ground-truth data for supervised classification can be challenging due to logistical, financial, or safety constraints. To address this limitation, several methods and strategies can be employed to ensure the classification remains accurate, even when direct field verification is not possible. For instance, historical data, government reports, or databases (e.g., land cover maps and vegetation databases) can serve as proxies for ground truth. These can be used to supplement or complement the limited data that is available (Gallant et al., 2018; Uhl et al., 2021; Henrys & Jarvis, 2019). The accessibility of satellite images with high resolution (Landsat, Sentinel, or commercial satellites) can provide a rich source of information to assist in identifying land cover types, even without ground-truth data. These images can be analyzed for spectral signatures and patterns that match the land cover classes being studied (Boyle et al., 2014). Experts can analyze remote sensing data based on their understanding of the region's characteristics, such as climate and vegetation types. This is crucial in areas where other data sources may be limited or unreliable. The interpretation process can be visual or digital, often requiring a combination of both methods to enhance accuracy (Gallant et al., 2018; Henrys & Jarvis, 2019).

Change detection techniques

The LULC change detection is the identification of deviations in an object's state through the estimation of temporal effects using multi-temporal data sets. Post-classification is among the commonly applied techniques for LULC change detection purposes (Singh, 1989). Numerous studies employ the Maximum Likelihood classification approach, classifying and labeling images from different dates, and extracting the area of change through direct comparison (Lu et al., 2004; Lunetta, 1999). This method needs both images to be individually rectified and classified before they can be compared pixel by pixel (Ji & Jensen, 1996). This method provides information and results in a base map that can be used for the subsequent year. Therefore, it identifies where and how much change has occurred.

Change detection analysis in LULC is a critical process for understanding how land use patterns evolve. This analysis typically involves comparing classified satellite images from different periods to quantify changes in LULC types, such as urban, forests, water bodies, & agricultural land. The choice of method for LULC change detection depends on the specific requirements of the study, including the scale of analysis, available data, and desired accuracy. Combining multiple methods can yield better results, particularly in complex landscapes where changes may be subtle or influenced by various factors.

The general equations for LULC change are commonly used in environmental studies to quantify changes over time:

$$\text{LULC change(ha/year)} = \left(\left(\text{Area}_{(\text{final year})} - \text{Area}_{(\text{initial year})}\right)/(\text{Time interval})\right)$$

$$\%\ \text{LULC change} = \left(\left(\text{Area}_{(\text{finalyear})} - \text{Area}_{(\text{initialyear})}\right)/\text{Area}_{(\text{initialyear})}\right) \times 100$$

where Area = the extent of each LULC category

% of LULC = Percent change in the area of a land use type

Area initial = the area of land used at the initial time;

Area final = the area of the same land use type at the final period, &

Time interval = time interval between the final and initial years.

Accuracy Assessment Metrics

Accuracy assessment is a critical component in LULC change detection, as it quantifies the reliability of classified images or change detection maps. This process involves comparing classified data against reference data, which is assumed to be true, to evaluate performance metrics, namely overall, user, & producer accuracy. The accuracy assessment typically involves creating a confusion matrix, which is a table that summarizes the degree of the cataloguing procedure by showing the correspondence between predicted classes and actual classes from reference data1. The confusion matrix allows for calculating various accuracy metrics and provides insights into specific areas where classification errors occur (Fresz et al., 2024; Feizizadeh et al., 2022).

The accuracy assessment reflects the real difference between our classification and the reference map or data (Pouliot et al., 2014; Tsutsumida & Comber, 2015). The assessment of classification results may be poor if reference data is highly inaccurate. Producer's accuracy refers to the map maker's accuracy in showing real features on the classified map, divided by the total number of reference sites (Gunathilaka & Fernando, 2022). User's accuracy is the map user's perception of the class's presence on the ground, calculated by dividing the total correct classifications by the row total. It represents errors of omission or exclusion, while producer's accuracy corresponds to commission or inclusion errors (Congalton, 2001; Wickham et al., 2019).

The kappa coefficient is a standard measure used in accuracy assessment and resolves the issue of chance agreement or the allocation of the correct class by chance. Many studies have recommended Cohen's Kappa coefficient to be the standard measure of classification accuracy. The Kappa statistic value is a degree of the agreement between classification and reference data (Mishra & Nitika, 2016; Wang et al., 2021; X. Li, 2010; Mishra et al., 2019). Landis & Koch, (1977) divided the kappa values, which ranged from 0 to 1, into three categories: (1) good agreement between the classification and reference data was defined as having a value greater than 0.80, (2) moderate agreement was defined as having a value between 0.40 and 0.80, and (3) low agreement was defined as having a value less than 0.40. According to Wongpakaran et al., (2013), Kappa coefficient is commonly multiplied by 100 to provide a percentage measure of classification accuracy. It normally varies from 0 to 1.00, where it indicates strong agreement.

Stehman (1997) argues that overall, users' & producers' accuracy are more applicable accuracy measures due to their direct interpretation as probabilities distinguishing data quality of a specific map and thus recommends all summary measures be used as each measure alone obscures potentially important details. This method of accuracy assessment comes with inherent assumptions and limitations. Generally, it is implied that each pixel belongs solely to one of the classes in a defined set of mutually exclusive classes (Kamusoko, 2022). It is argued that the Kappa coefficient is not always suitable as a chance agreement is overestimated and underestimates classification accuracy (Kamusoko, 2022). Each measure of accuracy assesses different components of accuracy and thus different assumptions about the data(Stehman, 1999). Additionally, there is no widely accepted measure of accuracy, but various indices, each sensitive to different features. Thus, there is no all-purpose measure of classification accuracy (Kamusoko, 2022). Sampling design is very important, as the confusion matrix cannot be properly interpreted otherwise. A basic sampling size, such as random sampling, is suitable only if the sample size is large enough to guarantee all classes are adequately represented (Kamusoko, 2022). All constraints in a particular study must be considered in the design process of an accuracy assessment. The design should be practical not to diminish the credibility of the derived accuracy statement (Stehman & Czaplewski, 1998).

Accurate assessment in LULC change detection is essential for effective land management and decision-making processes. Employing robust methodologies and understanding key metrics are crucial for enhancing classification accuracy and reliability in remote sensing applications. It not only validates the classification results but also enhances decision-making for land management by providing reliable information on land cover changes over time. Understanding and addressing challenges such as training data uncertainty are vital for improving the robustness of these assessments.

The Kappa coefficient is a statistical measure used to assess the agreement between two raters or the accuracy of classification models. While it is a valuable tool, it has notable limitations, particularly when applied to imbalanced datasets. One of the primary criticisms of the Kappa coefficient is its tendency to overestimate agreement in cases of class imbalance. When certain classes are overrepresented, Kappa can yield higher values, implying better performance than is meaningful. This occurs because the expected agreement due to chance increases with skewed class distributions, leading Kappa to suggest that a classifier is performing well even if it struggles with minority classes (Delgado & Tibau, 2019). Kappa's sensitivity to class proportions means that when one class dominates, the expected chance agreement rises, inflating the Kappa value despite poor overall classifier performance. This makes Kappa less reliable for evaluating classifiers on imbalanced datasets unless adjustments are made for these imbalances (Delgado & Tibau, 2019).

Challenges and Limitations

LULC change analysis faces significant challenges in data integration and validation, particularly when leveraging modern remote sensing technologies. Merging multi-resolution datasets for LULC classification faces fundamental challenges due to the lack of standardized classification systems, with existing frameworks often exhibiting incompatible class definitions, inconsistent threshold values, and spectral/spatial misalignment (Sudhakar & Rao, 2010). Combining datasets like Landsat-8 (30m) and Sentinel-2 (10m) introduces challenges due to spatial resolution mismatches. Resampling coarser data to match finer resolutions (e.g., Landsat to Sentinel-2) risks losing critical details and amplifying spectral mixing, especially in heterogeneous landscapes. Newer satellites (e.g., Pleiades, Sentinel-2) improve spectral diversity but require advanced fusion techniques to harmonize multi-resolution inputs (Vallet et al., 2024; Mashala et al., 2023). Satellites like Sentinel-2 and Landsat-8 struggle to provide simultaneous cloud-free imagery, complicating multi-temporal analysis. This mismatch hinders consistent monitoring of rapid changes, such as seasonal agricultural shifts or sudden deforestation (Mashala et al., 2023). Many models depend on historical patterns for short-term predictions, limiting their utility for long-term forecasting. Hybrid approaches combining machine learning (e.g., Random Forest, neural networks) with traditional methods are needed to process multisource data (LiDAR, radar) and reduce dependency on outdated spectral libraries (Lawal & Gulma, 2024).

Validation complexities arise from temporal mismatches between ground truth data and satellite acquisitions, compounded by manual interpretation biases and the limited scalability of field surveys (Sudhakar & Rao, 2010). Remote or inaccessible regions often lack updated ground-truth data, forcing reliance on outdated proxies like historical maps or low-resolution vegetation databases. This issue is acute in dynamic ecosystems where in-situ validation is sparse (Lawal & Gulma, 2024; L. Tan et al., 2024). Underrepresented classes (e.g., dispersed settlements) skew accuracy metrics like kappa coefficients, while mixed pixels (e.g., urban-vegetation blends) introduce ambiguity in validation. High-resolution imagery and object-based classification can mitigate these errors, but remain computationally intensive (Lawal & Gulma, 2024). Unsupervised methods require manual labeling of spectral clusters, which is error-prone in transitional zones (e.g., shrubland-grassland boundaries). Machine learning automates this process but struggles with rare or spectrally similar classes without robust training data (Lawal & Gulma, 2024). Prioritizing frequent dataset updates and integrating multi-temporal, high-resolution imagery will enhance LULC change detection accuracy, particularly for small-scale features and specific ecosystems.

2.1.4. Ecosystem service concepts and values

2.1.4.1 Definition and concepts

Ecosystem services refer to the benefits humans derive from natural ecosystems, reflecting the link between human welfare and ecosystems, with various definitions commonly used in natural resource management literature. The commonly cited definitions are as follows:

According to Daily, (1997), ecosystem services are the conditions and processes that sustain and fulfill human life, including the production of goods consumed by humans, cleansing, recycling, renewal, and providing intangible aesthetic and cultural benefits.

Ecosystem services, as defined by Costanza et al., (1997), are goods and services that humans extract from ecosystem functions, including materials, energy, and information, to support human wellbeing. De Groot et al., (2002) and De Groot et al., 2012) emphasize that ecosystem goods or services are conceptualized from observed ecosystem functions, based on anthropocentric perspectives, incorporating human values.

The MEA, (2005) defined ecosystem services as benefits provided by ecosystems, categorized into provisioning, regulating, cultural, and supporting services. Recent literature supports this definition, with a revised conceptual framework linking human societies and well-being with ecosystems, indirectly or directly (De Groot et al., 2010; De Groot et al., 2012; Costanza et al., 2014; TEEB, 2014). The definitions of ecosystem services, based on anthropocentric perspectives, differ in their definitions. However, they differ in several aspects. De Groot et al., (2002) and Daily, (1997) agree that ecosystem services include conditions, processes, and life-support functions, while MEA, (2005) defines them as human benefits from ecosystems.

Ecosystem services describe the benefits that nature provides for the well-being of people and society (Daily, 1997; MEA, 2005; TEEB, 2011). Biodiversity, comprised of species, genes, and ecosystems, is the foundation for the provision of ecosystem services (Cardinale et al., 2012). Ecosystem services include essential elements that support human life, namely food, water, & materials provision, water and climate regulation, maintenance of soil productivity, air quality, and carbon sequestration for climate regulation. The contribution of nature to aesthetics, spiritual inspiration, recreation, as well as science and traditional knowledge, is part of the cultural dimension of the services provided by the ecosystem. In essence, biodiversity provides benefits in the form of ecosystem services, which ensure the livelihoods of people and society at large. It is not gifts from nature (Spangenberg et al., 2015). Traditions, belief systems, political systems, markets, and regulations influence which ecosystem services are used and how. Hence, human agency determines what aspects of biodiversity and ecosystems are regarded to be ecosystem services and how these are used (Spangenberg et al., 2015). This process of human-nature interaction is shaping ecosystems and landscapes at local, national, and global scales. Therefore, knowledge of ecosystem services is useful for informing decisions on ecosystem management (Hancock, 2010; Daily et al., 2009). Ecosystems provide bundles of multiple ecosystem services, with the characteristics of the ecosystem service bundles differing between landscapes, management practices, and social-ecological systems (Raudsepp-Hearne et al., 2010). For example, provisioning services dominate in agricultural landscapes, while regulating services dominate in more natural landscapes (Foley et al., 2005). Information on ecosystem services can inform decision-makers on trade-offs involved in decision making, for instance, who gains & who loses as a result of LULC changes (Howe et al., 2014). Hence, facts and assessment on ecosystem services is in particular relevant for informing decisions on sustainable ecosystem management aiming at maintaining human wellbeing while conserving biodiversity (Goldman et al., 2008). Scientific research on ecosystem services has become popular over the last decades, with a substantive rise in published literature (Seppelt et al., 2011). The MEA identified that a range of indicators and data exists on the biophysical aspects of the services provided by terrestrial ecosystems; however, information on the economic dimension of ecosystem services is scarce (MEA, 2005). This has been regarded as a shortcoming in particular when it comes to informing decision-making, which is often based on expected economic impacts. Therefore, the international initiative on TEEB was initiated by the German government together with the European Commission and the UNEP, with the strong support of multiple donor countries. The primary focus of the TEEB initiative is to inform policymakers and decision-makers on the multiple values that ecosystems and biodiversity provide to society. The TEEB reports compiled existing data on ecosystem services' monetary and non-monetary value (De Groot et al., 2012), synthesized economic valuation methods TEEB, (2014), and guided.

The CBD, together with the UNFCCC, has been instrumental in mainstreaming a focus on ecosystem services based on the recognition that biodiversity & terrestrial ecosystems offer benefits to society and human health (Maes et al., 2012; Vihervaara et al., 2010). Hence, the concept is also instrumental in working towards achieving the Sustainable Development Goals (SDGs) (Griggs et al., 2013).

4.1.4.2 Classification of ecosystem services

Categorization of ecosystem services is a precondition for any attempt to measure, map, or value ecosystem services and to communicate the findings transparently (De Groot et al., 2017). Although many frameworks have been created to analyze ecosystem services, each author has their own classification system for these services. Ecosystem services require a well-defined classification scheme to facilitate effective measurement, valuation, and results distribution, which in turn promotes sustainable resource management. Therefore, it is critical to have standardized frameworks, a consistent and comprehensive assessment of the products and services, and ecosystem function. Various classification systems exist to facilitate this process, each with its framework and focus.

The most commonly used classification, provided by the MEA, is based on four categories: provision, regulation, supporting, and cultural services (MEA, 2005). The provision of services includes goods extracted from ecosystems such as timber, fuelwood, food, and fibers. Regulating services help maintain the regulation of ecosystem processes, including carbon sequestration and climate regulation, pest and disease control, and waste decomposition. Supporting services support the provision of all the other categories including soil formation, production of oxygen, nutrient & water cycling, & habitat provision whereas cultural services contribute to spiritual welfare such as recreational, spiritual, religious, and esthetic experiences (Wittmer, 2010; Haines-young & Potschin, 2011; Haines-Young & Potschin, 2018). The second commonly used classification is the TEEB study applies a similar classification approach as proposed by MEA, distinguishing provisioning, regulating, and cultural services, while the fourth category labeled habitat or supporting service cover sites for species and maintenance of genetic diversity i.e. an alternative classification replacing the category of supporting services with habitat services including nursery and gene pool functions (De Groot et al., 2012). More recently, the Common International Classification of Ecosystem Services (CICES) provided standardization in the way ecosystem services are described to overcome a translation problem between different classification systems, which are not always comparable due to different perspectives or definitions of the categories (www.cices.eu). The CICES is hierarchically organized, and it applies the three major sections of services provisioning, regulating, and cultural, defined basically in the same way as in the MEA and TEEB classification, and then splits them further into divisions, groups, and classes. The hierarchical structure enables users to combine data for comparisons or more generalized reports, and cultural ecosystem services, downcast to the most suitable level of detail (Burkhard and Maes, 2017; Haines-Young & Potschin, 2018).

2.1.4.3 Ecosystem services valuation methods

There are three different ways to assess the value of ecosystem services: qualitative analysis, quantitative analysis, and monetary analysis (TEEB, 2011). According to Kettunen et al., (2012), the qualitative analysis focuses on non-numerical value indicators, such as benefits to mental and physical health, and social benefits from recreation. The quantitative analysis focuses on numerical data such as the quantity of sequestered carbon, the quality of water, etc. Monetary analysis focuses on translating the qualitative and quantitative aspects of a particular currency. Ecosystem service valuation in monetary terms is the most widely applied approach (Selivanov & Hlaváčková, 2021; Christie et al., 2012), as it is often deemed to be the most pragmatic language when it comes to communication with political and business institutions (Spash, 2013). There are numerous methods used to evaluate ecosystem services, with monetary valuation methods being the most widely applied. The main goal of ecosystem services valuation is to enhance the ability of decision-makers to evaluate trade-offs between alternative ecosystem management regimes and courses of action that alter the utilization of ecosystems and the benefits they offer (Pandeya et al., 2016).

Ecosystem service valuation utilizes various methods and approaches for evaluation of ESV (S. Liu et al., 2010). These methods include direct market valuation methods (market-price–based method, cost-based valuation method, & production function), indirect-market valuation techniques or revealed preferences, & non–market valuation methods or stated preference (contingent valuation methods, Choice modeling methods, and group deliberation) (Koetse et al., 2015). In general, monetary valuation provides a common unit for comparing ecosystem services and communicating with political and business institutions (Selivanov & Hlaváčková, 2021a). However, it has limitations in fully capturing the complexity of ecosystems and the diversity of values held by different stakeholders (Pandeya et al., 2016; Pascual et al., 2012). Combining multiple valuation methods, both monetary and non-monetary, can provide a more comprehensive assessment of ecosystem services (Pandeya et al., 2016). Careful consideration of the timeline and assumptions is also crucial when evaluating ecosystem services (Pandeya et al., 2016; Anil Markandya, 2019).

Monetary valuation methods are crucial for assessing the ESV, which are categorized into provisioning, regulating, cultural, & supporting services. These methods help in decision-making and policy development by quantifying the economic benefits derived from these services. The ecosystem services most frequently valued using these methods include Provisioning Services: These services provide direct benefits to humans, such as food, water, and raw materials. They are often valued using direct market methods, such as market prices and cost-based valuation techniques (Selivanov & Hlaváčková, 2021b; Briceno, 2023). Regulating Services: These include services that regulate natural processes, such as climate regulation, flood control, and water purification. Valuation methods for regulating services often involve both direct cost-based approaches and indirect market methods, like hedonic pricing and travel cost methods (Selivanov & Hlaváčková, 2021b). Cultural Services: These services encompass non-material benefits, such as recreational, aesthetic, & heritage. Non-market valuation methods, particularly contingent valuation and choice modeling, are frequently used for these services due to their non-tradable nature. Supporting Services: These services, which include nutrient cycling and soil formation, are essential for the functioning of ecosystems but are often indirectly valued (Selivanov & Hlaváčková, 2021b). They may be assessed using direct market methods or through more complex valuation approaches that consider their contribution to other ecosystem services (Pascual et al., 2010; Selivanov & Hlaváčková, 2021b; Burkhard and Maes, 2017).

One approach to estimating ecosystem service values is to use global average values. While global average values provide a useful starting point for quantifying ecosystem service values, it is essential to take into account the restrictions and unknowns surrounding this type of approach. Combining global estimates with local data and addressing methodological challenges can lead to more accurate and context-specific assessments of ESV and their changes over time (Cheng et al., 2022; Birhane et al., 2024). Following the release of Costanza et al. (1997), who suggested a list of ecosystem service value coefficients of biomes (LULC types) and estimates of global ESVs, there has been a lot of interest in quantifying ecosystem service values and their fluctuations (Kindu et al., 2016). While considerable efforts have been made to estimate ESVs and suggest options for areas with scarce data, such studies are lacking for many countries in Africa, including Ethiopia, that have dramatic LULC dynamics (Birhane et al., 2024; Mathewos & Aga, 2023; Shiferaw et al., 2021; Haileslassie et al., 2024; Leh et al., 2013).

Deriving coefficients for ecosystem service values with a higher local validity for Ethiopia and addressing spatial variation in ecosystem service values through quantitative knowledge is limited (Kindu et al., 2016). Therefore, quantification of the evaluation of the ecosystem based on land use dynamism is important for Ethiopia to determine the monetary value of the natural resources found in the watershed. However, the use of monetary valuation for ecosystem services can indeed lead to oversimplification, failing to capture the full complexity of ecosystems and raising ethical concerns about assigning monetary values to nature (Schmidt et al., 2016; Hejnowicz & Rudd, 2017). There is significant variability and uncertainty in monetary valuations due to differences in site characteristics, socio-economic factors, and valuation methods. This can result in errors when transferring values across different locations or contexts (Horlings et al., 2020; Hejnowicz & Rudd, 2017).

Assigning ESV can be seen as commodifying nature, which may not align with ethical or cultural perspectives that value nature beyond economic terms (Hejnowicz & Rudd, 2017). Many ecosystem services are public goods or common-pool resources, which cannot be easily privatized or traded in conventional markets. This challenges the notion of assigning market prices to these services. Decisions involving ecosystem services often implicitly value them, but this valuation is not always transparent or equitable. Explicit monetary valuation can highlight these trade-offs, but may also overlook non-economic values (Hejnowicz & Rudd, 2017). Using a combination of quantitative and qualitative methods can help capture a broader range of ecosystem values and complexities (Hejnowicz &

Rudd, 2017; Selivanov & Hlaváčková, 2021b). Valuations should be spatially and temporally explicit to reflect the specific contexts in which ecosystem services are provided and used (Briceno, 2023). It is crucial to communicate the uncertainties associated with monetary valuations to decision-makers, ensuring that these values are used as part of a broader decision-making framework rather than as the sole basis for policy (Hejnowicz & Rudd, 2017; Schmidt et al., 2016).

2.1.4.4 Applications in policy and decision-making

The ESV plays a significant role in decision-making by providing a framework to assess the economic and non-economic benefits of ecosystems. This valuation helps policymakers evaluate trade-offs between different management strategies & communicate the importance of ecosystem conservation in economic terms. Ecosystem service valuation is used in Cost-Benefit Analysis (CBA) to assess the costs and financial advantages of initiatives or policies, ensuring that environmental impacts are considered alongside economic ones (McFarland & Gerdes, 2016). It helps in regulatory reviews by providing a monetary value for ecosystem services affected by regulatory changes. Valuation methods can also identify and quantify environmental externalities, which are costs or benefits not reflected in market prices, allowing policymakers to internalize these costs in decision-making. By integrating ecosystem values into policy frameworks, valuation can support the preservation, sustainable management, and restoration of ecosystems, which aids in developing new policy measures that account for the economic and non-economic benefits of ecosystems. While monetary valuation is effective for communicating with policymakers, it may not fully capture the complexity and diversity of ecosystem values, particularly cultural and non-use values (Nijnik & Miller, 2017). However, using a combination of monetary and non-monetary techniques can offer a more thorough assessment of ecosystem services, addressing the limitations of each approach.

2.1.4.5. Invest as a tool for ecosystem service evaluation

InVEST is a spatially explicit tool to model and map ecosystem services caused by land cover changes (Tallis & Polasky, 2009; Polasky, 2011). The InVEST model allows us to analyze trade-offs among ecosystem services across different scenarios in the past, current, & future LULC change (Dang et al., 2021; Tallis et al., 2011). The InVEST model is the baseline for quantifying ecosystem services as a GIS tool developed by Stanford and Minnesota Universities, the World Wildlife Fund, and The Nature Conservancy. This geospatial tool helps to evaluate the land-use change impact on ecosystem services (Duarte et al., 2016) and is used to model ecosystem services of the forest like soil erosion protection/sediment retention, carbon storing, & sink, water resources, timber, & NTFPs. The model is run with ArcGIS software environments, LULC data, and other spatial data to quantify provision services as well as the locations and activities of people who benefit from services. The scale is flexible, can be used at the local or regional levels, and is designed to work with terrestrial ecosystems (Bagstad et al., 2013). It gives biophysical & monetary value to each ecosystem services (Salata et al., 2017).

Ecosystem services valuation is a multifaceted process that utilizes diverse methodologies to quantify the benefits provided by natural ecosystems. Understanding these values is crucial for effective environmental management and policy development, especially in regions facing rapid land use changes. The integration of various valuation approaches can lead to more informed decisions that reflect both economic needs and ecological sustainability. By integrating ecological data with economic valuation techniques through its modular design, InVEST effectively combines different valuation methods to assess ecosystem services comprehensively. This integration supports decision-makers in understanding trade-offs and impacts associated with land use changes, ultimately aiding in sustainable resource management.

While the InVEST model is a valuable tool for ecosystem service assessments, its outputs are subject to limitations related to data quality, model assumptions, and operational constraints. The performance of the InVEST model heavily depends on the quality and accuracy of the input data. High-quality data is crucial for reliable outputs, but data limitations can lead to inaccuracies in the predictions of the model (Hamel et al., 2024). The time and place resolution of the data may limit the model's efficacy. For instance, if the data resolution is too coarse, it may not capture local variations effectively (Hamel et al., 2024). Like many models, InVEST relies on assumptions about ecosystem processes and their interactions. These assumptions can introduce biases if they do not accurately reflect real-world conditions. While InVEST is designed for general use, its applicability might be limited in certain contexts due to its structure and assumptions. It may require customization or additional data to be effective in diverse settings (Hamel et al., 2024). If the input data does not adequately represent all relevant ecosystem services or conditions, the model's outputs may be biased towards the well-represented aspects.

Addressing these limitations through improved data collection, model refinement, and careful interpretation of results is essential for maximizing the model's utility. Conduct sensitivity analyses to understand how variations in input parameters affect model outputs. This helps identify critical data points and assumptions that significantly impact results. Focus on gathering high-resolution, accurate, and comprehensive data. This includes using advanced RS technologies & observations to improve the space and temporal resolution of input data (Fer et al., 2021). Implement rigorous validation processes to ensure that the data accurately represents the ecosystem conditions being modelled (DeAngelis et al., 2021; Fer et al., 2021). Incorporating more complex ecosystem interactions and using scenario planning helps address assumptions and explore various future conditions (DeAngelis et al., 2021; Fer et al., 2021). Additionally, quantifying uncertainty with methods like Monte Carlo simulations and transparently communicating these uncertainties to stakeholders ensures informed decision-making. A collaborative, iterative approach that engages stakeholders and continuously refines the model based on new data further enhances its reliability and relevance (DeAngelis et al., 2021; Fer et al., 2021).

2.2. ESTIMATION OF CARBON STOCKS

Estimating landscape carbon is essential for understanding carbon sequestration and its implications for climate change mitigation. Various methodologies have been developed to assess carbon stocks in different ecosystems, including forested areas. Allometric equations are traditional tools used to estimate forest carbon stocks. They relate the size of trees to their biomass, allowing for the calculation of carbon content based on biomass estimates. While effective, these methods often require destructive sampling, which can be impractical for protected species or in sensitive environments (Vargas-Larreta et al., 2017). Recent advancements in remote sensing technologies offer complementary or alternative methods for estimating carbon stocks. Techniques such as satellite imagery, laser scanning, and photogrammetry enable researchers to gather data over large areas without the need for extensive fieldwork. Remote sensing can be integrated with local allometric equations to enhance accuracy and provide ground-truth validation (Batsaikhan et al., 2020; Vicharnakorn et al., 2014).

Field measurements remain essential for validating remote sensing data. These measurements are often supplemented by spatial interpolation techniques, such as kriging or bicubic splines, which help estimate carbon stocks across landscapes based on sampled data points. This approach is particularly useful in fragmented or heterogeneous landscapes where direct measurements may be limited. Carbon stocks in landscapes can be categorized into two main pools: aboveground biomass (living and dead vegetation) and belowground biomass (soil organic matter). Accurate assessments require detailed estimations of both pools, as they play significant roles in the global carbon cycle. For instance, tropical forests are known for their high carbon density and potential for carbon sequestration, highlighting the importance of precise biomass estimations in these ecosystems (Sulistyawati et al., 2006).

Quantifying global terrestrial carbon involves assessing two primary carbon pools: above-ground carbon in vegetation biomass and below-ground carbon in soil. Various organizations, including IPCC, UNEP/WCMC, & the Terrestrial Carbon Group (TCG), have published data on these carbon pools. However, discrepancies among these datasets can arise due to different methodologies used in measuring vegetation and soil carbon. However, there are differences between the data sets. The differences may arise from different measurements of vegetation or soil and disturbance (Rayden et al., 2010; Brown et al., 2021; Wang, 2019; Moon et al., 2024; Bekure, 2012). A major constraint to successful carbon offset programs is the lack of reliable, accurate, and cost-effective methods for monitoring carbon storage. If carbon becomes an internationally traded commodity, as it appears likely, then monitoring the amount of carbon fixed by projects will become a critical component of any trading system (MacDicken, 1997a).

Forests have traditionally been used for many products, including timber, fuel, and fodder. Determining the biomass of forests is a useful way of providing estimates of the quantity of these components. Typically, the quantity of sawn timber has been assessed by making volume estimations, but this ignores the other useful components, such as smaller-sized wood for fuel use. Furthermore, very few to no assessments have been made of the quantity of wood present in forests that appear to have no potential for sawn timber production. Assessing the total aboveground biomass of forests, defined as biomass density when expressed as dry weight per unit area, is a useful way of quantifying the amount of resource available for all traditional uses (Brown, 1997).

The accurate estimation of biomass in tropical forests is crucial for many applications, from the commercial exploitation of timber to the global carbon cycle. Particularly in the latter context, the estimation of the total above-ground biomass with an accuracy sufficient to establish the increments or decrements in carbon stored in the forest over relatively short periods is increasingly important (Basuki et al., 2009). Conventional forest inventory is one way of forest biomass estimation. However, the purpose of the inventory is mainly to estimate the merchantable volume of logs. One way to estimate how much carbon is in an acre/hectare of forest land is possible by clearing one acre of forest, measure the weight of all organic material harvested, and then analyze the material for the percentage of carbon in it. Though it would give a very precise estimate, it is not a very ecologically friendly way to study nature. A less harmful way to carry out this estimate is to develop an allometric equation that will allow us to estimate the mass of a tree from a few simple measurements of it, and then apply this equation to the trees in a forest. The term allometric is defined as the measure and study of the relative growth of a part of an entire organism or of a standard. It is based upon a principle first described by Galileo Galilee in the 1630s about how the proportions of an organism must change as it gets bigger. Regression models are used to convert inventory data into an estimate of aboveground biomass, but one of the large sources of uncertainty in all estimates in tropical forests is the lack of standard models for converting tree measurements to AGB estimates (Vieira et al., 2008; Chave et al., 2014; Chave et al., 2005). Allometric models are important for quantifying biomass and carbon storage in terrestrial ecosystems. Generalized allometric equations exist for tropical trees, but species- and site-specific models are more accurate(Litton & Kauffman, 2008; Henry et al., 2010). Generic equations, stratified by ecological zones, for estimating aboveground biomass exist, but they may not accurately reflect the tree biomass in a specific area or region(Segura & Kanninen, 2005).

In forestry, allometric algorithms are commonly utilized to calculate carbon stocks by relating easily measurable tree dimensions, namely, height, wood density, and DBH, to biomass and carbon content. The absence of known allometric relations for timber, for example, from Central Africa (including large-diameter trees and root fractions), presents a major difficulty in estimating forest biomass stocks. These gaps are partly due to the difficulty in financing the acquisition of data, which is not typically undertaken even in countries with established national forest inventories. What little data that are available are often not shared and difficult to compare due to differing collection protocols. However, very few allometric equations exist for sub-Saharan Africa, and as a result, generalized allometric equations, often established for forests in other continents, are used by default for wood density (Henry et al., 2010).

Developing allometric relationships for estimating forest carbon stocks is challenging due to the need for destructive harvesting & the diversity of forest tree species. While species-specific models are ideal, generalized models can be effective if they account for key variables like diameter and height (Avalos et al., 2022). However, applying models across different regions or species can lead to inaccuracies due to variations in growth patterns and wood density (Mulatu et al., 2024; Edae & Soromessa, 2019). The degree of precision of these equations depends on the original data's quality and representativeness. Inaccurate measurements can lead to significant errors in carbon stock estimation (Walker et al., 2016). Tree growth is also influenced by environmental variables including soil quality and rainfall, but these are frequently overlooked in models (Oumasst et al., 2024; Mulatu et al., 2024). Wood density varies significantly between and within species, based on factors like growth conditions and age. Using generalized wood density values can introduce errors (Walker et al., 2016). Recent studies have shown that incorporating more species and environmental factors can improve model accuracy, as seen in the development of palm-specific models, which highlight the importance of including diverse life forms in carbon stock estimates (Avalos et al., 2022).

More than 95% of the variation in aboveground tropical forest carbon stock can be explained by stratifying large forest types or ecological zones in the tropics using species groupings and generalized allometric correlations (Segura & Kanninen, 2005; Brown, 2002). Forest carbon stocks can also be evaluated using remote sensing instruments mounted on satellites or airborne platforms, but substantial refinements are needed before routine assessments can be made at national or regional scales. A major benefit of a satellite-based approach is the potential to provide wall-to-wall observation of proxies (Gibbs et al., 2007). Using generalized linear equations for carbon stock estimation in regions with unique ecological conditions can lead to errors such as ecological fallacy, model specification bias, errors in variables, and assumption violations (Gao et al., 2015; Bailey et al., 2013). These issues arise because generalized models often fail to capture local variability, including non-linear relationships and unique environmental factors (Gao et al., 2015). To mitigate these errors, it is crucial to supplement generalized models with local data and employ flexible modeling approaches that account for the distinct characteristics of each region (Magnussen & Carillo Negrete, 2015; Hoover & Smith, 2016). This approach can help improve the accuracy and reliability of carbon stock estimates by addressing the limitations of generalized models and ensuring that local ecological nuances are properly considered (Magnussen & Carillo Negrete, 2015; Hoover & Smith, 2016).

2.2.1. Aboveground biomass carbon stock

Above-Ground Biomass (AGB) includes all biomass in living vegetation, both woody and herbaceous, above the soil, including stems, stumps, branches, bark, seeds, and foliage. Above-ground biomass is the most visible of all the carbon pools, and changes in it are an important indicator of change or the impact of an intervention on benefits related to both carbon mitigation and other matters. Above-ground biomass is a key pool for most land-based projects. The features and the need for measuring and monitoring above-ground biomass, its importance to the national greenhouse gas inventory, and different project types, as well as the frequency of measurement of the pool. Carbon sequestration can be defined as removing CO_2 from the atmosphere and storing it in green plant biomass (sink) where it can be stored indefinitely through photosynthesis (Watson et al., 2000; Ali et al., 2023; IPCC, 2000). These sinks can be above-ground biomass (trees), living biomass below the ground in the soil (roots and microorganisms), or in the deeper sub-surface environments (Nair et al., 2009). Forests are major contributors to terrestrial carbon sinks, mitigating climate change and associated economic benefits (Watson et al., 2000; FAO, 2006).

Aboveground biomass carbon stock is mainly estimated by traditional field measurements or remote sensing methods. Different approaches, based on field measurement (Brown et al., 1989; Brown & Iverson, 1992; Brown, 2002) and remote sensing (Foody, 2003; Lu, 2006, Zheng et al., 2004), and GIS (Brown & Gaston, 1995) have been applied for AGB estimation. Traditional field sampling remains a reliable method for estimating AGB. This involves measuring the biomass of a sample of trees and extrapolating the data to larger areas. While accurate, this method can be labor-intensive and time-consuming.

2.2.2. Belowground biomass carbon stock

Below-Ground Biomass (BGB) carbon stock refers to the amount of carbon stored in plants' roots and other underground components. This carbon pool is critical for understanding terrestrial ecosystems' total carbon sequestration potential, as it contributes significantly to the overall biomass carbon stock. Globally, belowground biomass is estimated to account for 20–26% of the total biomass, and as such, it is an important carbon pool for many vegetation types and land-use systems. However, belowground stocks are poorly estimated, and hence the potential of tropical forests to mitigate climate change remains a major source of uncertainty. Precise determination of belowground biomass is a critical component of many applications, especially in quantifying C stocks, sequestration rates (Robinson, 2007; Temesgen et al., 2015), and the global carbon cycle (Huy et al., 2019).

Estimating belowground biomass often relies on allometric equations, which relate aboveground biomass to belowground biomass. A common ratio used is 0.2, meaning that belowground biomass is estimated to be about 20% of aboveground biomass (MacDicken, 1997). This method allows for the calculation of carbon stocks based on easily measurable parameters like DBH and wood density (Fradette et al., 2021; Singnar et al., 2021). Globally, BGB is estimated to account for 20% of total biomass, highlighting its importance across various vegetation types and land-use systems. This estimation method allows researchers to calculate carbon stocks based on easily measurable parameters such as DBH and wood density.

2.2.3. Soil organic carbon stock

An important part of soil health and a major contributor to the global carbon cycle is soil organic carbon. Since SOC affects both carbon sequestration and GHG emissions, an understanding of it is crucial for mitigating climate change (Georgiou et al., 2022). SOC contributes to various ecosystem services, including nutrient cycling, water retention, and erosion resistance. According to (Stockmann et al., 2013), SOC contains roughly 2344 Gt of organic carbon worldwide, making it the largest carbon (C) stock in the majority of terrestrial ecosystems (Lal, 2004; Bal et al., 2018). Furthermore, soil is acknowledged as one of the most significant parts of the biosphere, providing significant ecosystem services and functions, and is the principal carbon pool after the oceans (Ogle et al., 2005).

Several methods are used to measure soil organic carbon concentration, each with its own principles and applications. The most common methods include the Walkley and black methods, dry combustion, loss on ignition (gravimetric method), photometric method, and size and density fractionation (Johns et al., 2015; Olson et al., 2014; McCarty et al., 2010; Nelson & Sommers, 2018). The Walkley and black method is widely used for measuring SOC. It involves oxidizing soil organic matter using potassium dichromate ($K_2Cr_2O_7$) in an acid medium. The amount of remaining dichromate is titrated with ferrous sulfate, which is inversely related to the amount of carbon present in the soil sample (Walkley & Black, 1934). This method is effective for assessing the organic component of carbon in soil. In the dry combustion method, soil samples are combusted at high temperatures (around 975°C) in the presence of oxygen. The carbon in the soil is converted to carbon dioxide, which is then measured. This method is precise and can provide total carbon content, including inorganic carbon, if not pre-treated. The loss on ignition (gravimetric method) involves heating soil samples to a specific temperature (typically around 400°C) to burn off organic matter. The weight loss corresponds to the amount of organic carbon present. It is a simpler and less expensive method, but may not be as accurate as others. The photometric method also uses potassium dichromate for oxidation but measures the resulting solution's absorbance using a spectrophotometer. The absorbance is correlated with the concentration of organic carbon in the soil sample. Size and density fractionation methods involve physically separating soil particles based on size or density to analyze different fractions of organic carbon (e.g., particulate, humus). While they provide detailed insights into SOC dynamics, they are labor-intensive and complex. The most accurate and reliable way to measure soil organic carbon is careful, repeated direct field sampling followed by laboratory analysis using a dry combustion analysis and bulk density measurement. Direct sampling and dry combustion analysis are required to calibrate and validate modeling and high-tech field methods, such as spectroscopy, to reduce the volume of direct samples required in sampling rounds after the baseline is established and therefore reduce project costs (Walkley & Black, 1934; Renzas & Marín-Spiotta, 2012; Donovan, 2013).

2.3. Vegetation Index

A vegetation index is a quantitative measure used in RS to assess the bulk density & healthiness of vegetation in a specific area. Vegetation indices, derived from satellite imagery, are crucial for monitoring, plotting, and resource management of terrestrial ecosystems. They provide radiometric measures of vegetation's amount, structure, and condition, serving as indicators of seasonal and interannual variations. They also act as intermediaries in assessing leaf area index, green leaf area index, and photosynthetic activity (Huete et al., 1997; Huete, 1987). The main purpose of a vegetation index is to give a single value that reflects the greenness of vegetation, which correlates with its health and density. This is achieved through mathematical transformations of multiple spectral bands, particularly focusing on the red and NIR wavelengths. Healthy green vegetation receives the greatest of the visual radiation & reflects a significant portion of NIR light, allowing for effective differentiation from other surfaces like soil and water (Huete et al., 1997; Xue & Su, 2017; Ganie M A and Nusrath, 2016).

Vegetation indices, using red and near-infrared reflectance, monitor Earth's surface vegetation fluctuations since the 1960s. Measurements include leaf area index, green cover, chlorophyll content, biomass, and absorbed photosynthetically active radiation (APAR). Bannari et al., (1995) assert that Vegetation indices are categorized based on factors such as spectrum number, computation method, and historical growth. Yuan et al. (1998) and Lloyd (1990) categorized seven vegetation indices using hyperspectral remote sensing technology, which provides high-resolution reflectance spectra for multispectral indices and narrow-band indices for hyperspectral data.

Vegetation indices are essential tools in remote sensing, providing insights into vegetation health, density, and type across various LULC categories. Different vegetation indices are used to analyze diverse types of LULC, including forests, grasslands, agricultural areas, and urban landscapes. Their ability to provide insights into vegetation health and density makes them crucial for effective resource management and environmental monitoring. As technology advances, particularly with hyperspectral remote sensing, new indices tailored for specific applications continue to emerge, enhancing our understanding of terrestrial ecosystems.

2.3.1. Normalized difference vegetation index

The NDVI is the difference between NIR and visible red values of reflectance normalized over reflectance and calculated from reflectance measurements in the NIR and red regions (Burgan & Hartford, 1993). To calculate the NDVI, subtract the red band from the near-infrared & then divide by the near-infrared plus the red band. The range of the value is -1 to 1; the negative values are indicative of water, snow, clouds, non-reflective surfaces, and other non-vegetated areas, while the positive value expresses reflective surfaces such as vegetated areas (Burgan & Hartford, 1993).

The NDVI is a critical metric used in remote sensing to assess vegetation density & health. It is calculated using reflectance measurements from two specific spectral bands: the NIR & the red spectrum portion.

NDVI = (NIR-R)/(NIR+R),

where R is the red band and NIR is the near-infrared band. Greyscale raster maps with index values between +1 & -1 make up the NDVI map. An extremely negative value refers to the water content; values closer to zero refer to bare land, and the highest represents green vegetation (Z. Tan et al., 2015). This formula normalizes the difference between the NIR and red reflectance values, allowing for a standardized vegetation assessment across different conditions and locations. The NDVI scale runs from -1 to 1, with a value near 1 denoting thick, healthy vegetation, a number near 0 denoting arid regions, and a value below 0 usually indicating water or clouds (M. Abdusamea, 2024).

NDVI helps as a powerful means for RS applications, providing insights into vegetation health and environmental conditions through its straightforward calculation and interpretation of reflectance data. The NDVI is a valuable tool for assessing vegetation health, but it has several limitations that can affect its accuracy and applicability. NDVI values can be significantly influenced by atmospheric factors such as cloud cover, pollution, and shadow effects. These conditions can distort reflectance measurements, leading to inaccurate NDVI calculations unless proper correction techniques are applied (Adams et al., 2021; Vélez et al., 2023). The accuracy of NDVI calculations is extremely based on the quality & spatial resolution of remote sensing information. Poor-quality data can significantly hinder results (Vélez et al., 2023).

2.3.2. Soil-adjusted vegetation index

The Soil-Adjusted Vegetation Index is a vegetation index designed to reduce the influence of soil brilliance on vegetation measurements, especially in regions with little vegetation. The SAVI is structured similarly to the NDVI but with the addition of a soil brightness correction factor. L is the brightness of the soil correction variable, RED is the reflection factor of the red band, and NIR is the reflection factor value of the near-infrared band. The green vegetation cover affects L; in places with extremely dense vegetation, L= 0, and in areas without any green vegetation, L= 1. Generally, an L= 0.5 works well in most situations and is the default value used. When L= 0, then SAVI = NDVI. The introduction of the correction factor L allows SAVI to adjust for varying soil conditions, making it more reliable than NDVI in certain environments (Huete, 1988; Huete, 1999; Huete, 1987).

SAVI is equal to ((NIR-R)⁄(NIR+R+L) *(1+L)).

where L is the correction factor, R is the red band, NIR is the near-infrared band, and SAVI is the soil-adjusted vegetation index.

SAVI represents a significant advancement in the field of RS, allowing for more precise assessments of vegetation in challenging environments where traditional indices may fail. It is specifically designed to mitigate the effects of soil brightness on vegetation measurements. This index is particularly useful in areas with sparse vegetation, where indices like the NDVI may yield inaccurate results due to soil interference. The SAVI represents a significant advancement in remote sensing technology, allowing for more reliable assessments of vegetation in challenging environments. By effectively minimizing soil brightness effects, SAVI enhances our ability to monitor and manage agricultural and ecological systems (Vani & Mandla, 2017).

2.3.3. Enhanced vegetation index

The EVI is a refined vegetation index that improves the measurement of vegetation density & health, particularly in areas with high biomass. It improves upon the NDVI by correcting for atmospheric conditions & background noise, making it especially useful in dense vegetation environments (Huete, 1999; Huete et al., 1997).

EVI is equal to 2.5 * ((NIR - RED) / (NIR + C1 * RED - C2 * BLUE + L)), where NIR stands for near infrared band, RED for red band, BLUE for blue band, L: value to correct for canopy backdrop (0, 0.5 & 1), C1: values as constants for atmospheric resistance to change: Value 6, and C2: values as constants for atmospheric resistance to change: Value 7.5.

The EVI represents a significant advancement in the field of vegetation monitoring. By providing a more accurate and robust alternative to NDVI, particularly in complex environments, EVI enhances our ability to assess plant health and inform agricultural practices, forest management, and conservation efforts. Its integration into satellite imagery analysis continues to transform how we understand and manage Earth's vegetation resources. It is a robust metric for monitoring changes in natural ecosystems. Its ability to accurately reflect vegetation health and density makes it a valuable resource for researchers and environmental managers aiming to understand and manage ecological changes effectively.

2.3.4. Landscape carbon stock estimation using vegetation indices

Estimating carbon stocks in landscapes is crucial for understanding carbon dynamics and informing climate change mitigation strategies. This process often utilizes vegetation indices, which are a statistical combination of satellite imagery's spectral reflectance data to efficiently estimate carbon stocks and biomass. NDVI is widely used for estimating AGB due to its strong correlation with vegetation density and health. Studies have shown that NDVI can effectively predict AGB in various ecosystems, including urban landscapes, with high coefficients of determination (R^2) ranging from 0.64 to 0.87, depending on the land use type (Batsaikhan et al., 2020; Habib & Al-Ghamdi, 2021). EVI is another significant index that improves sensitivity in high biomass regions and minimizes atmospheric influences. It is particularly useful in areas with dense vegetation where NDVI may saturate (Pandapotan Situmorang et al., 2016a). SAVI is designed to reduce soil brightness influences, making it more suitable for sparse vegetation areas. This index can provide more accurate biomass estimations when foliage cover is limited (Habib & Al-Ghamdi, 2021).

Indirect methods involve establishing relationships between VIs and direct biomass measurements through regression analysis. This approach allows for scaling up from plot-level data to larger landscape estimates while accounting for variability in vegetation cover. Utilizing vegetation indices for landscape carbon stock estimation offers a robust framework for monitoring and managing carbon dynamics across different ecosystems. By combining RS methods with direct-ground measurements, scholars can achieve more accurate and scalable assessments of carbon stocks, contributing to effective climate change mitigation strategies. Overall, while vegetation indices like NDVI and EVI are effective tools for estimating carbon stocks, their accuracy can be influenced by factors such as biomass density and environmental conditions. EVI is noted for its ability to reduce background noise and atmospheric interference, making it more reliable than NDVI in dense vegetation areas. Studies suggest that EVI may provide more accurate biomass estimates compared to NDVI, particularly where saturation effects are pronounced. Combining VIs with additional data sources like LiDAR can significantly improve estimation precision, addressing issues like saturation and providing a more comprehensive understanding of carbon dynamics across landscapes.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. DESCRIPTION OF STUDY SITE

3.1.1. Location

The Awash River basin is a significant river basin entirely contained within the country, covering approximately 1,200 kilometers and discharging into the salty Lake Abbe near the Djibouti border (FAO and IHE Delft, 2020; Taddese & Peden, 2009). It is an important water resource for irrigation, domestic use, and other economic sectors (Assegide et al., 2022). The Upper Awash River Basin is situated in the central region of the Oromia National Regional State in Ethiopia. This area extends from the Chilimo-Gaji Forest downstream to the Menagesha Suba Forest, covering an approximate area of 2827 km². The geographical boundaries are defined by latitudes of 8° 40' 00'' to 9° 10' 00'' N and longitudes of 38° 00' 00'' to 38° 40' 00'' E. The basin's elevation ranges from 2290 to 3300 meters above sea level (Figure 2).

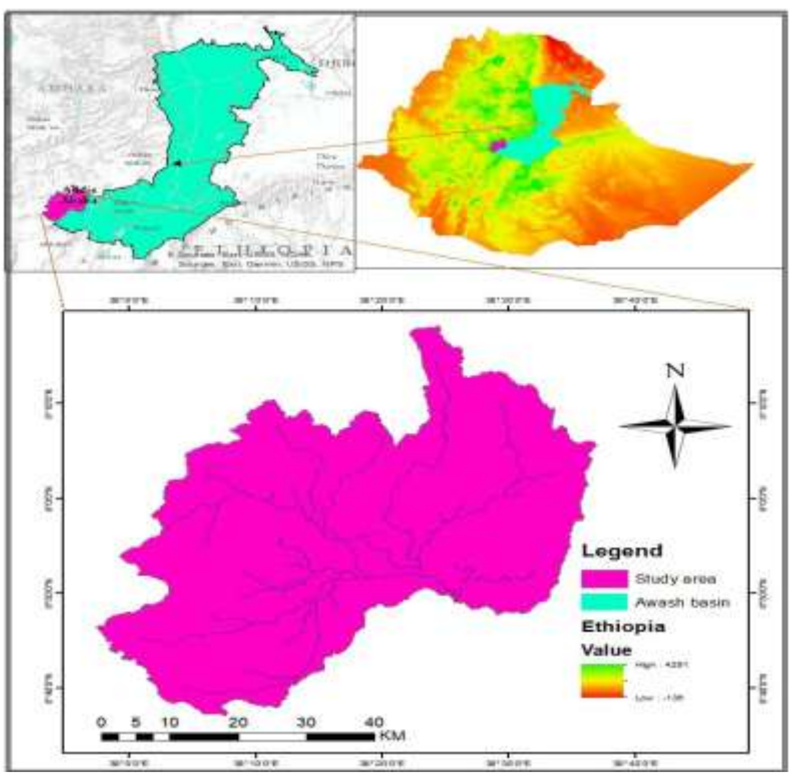


Figure 2. Location of the Upper Awash Basin

3.1.2. Climatic characteristic (RF & T)

The Upper Awash River Basin experiences a bimodal rainfall distribution, receiving about 1250 mm of annual rainfall with a primary rainy season between June & September & a secondary season between March & May. The average annual temperature fluctuates between 13.55 °C and 25.2 °C, with cooler temperatures in November and December and warmer conditions in May (Figure 3).

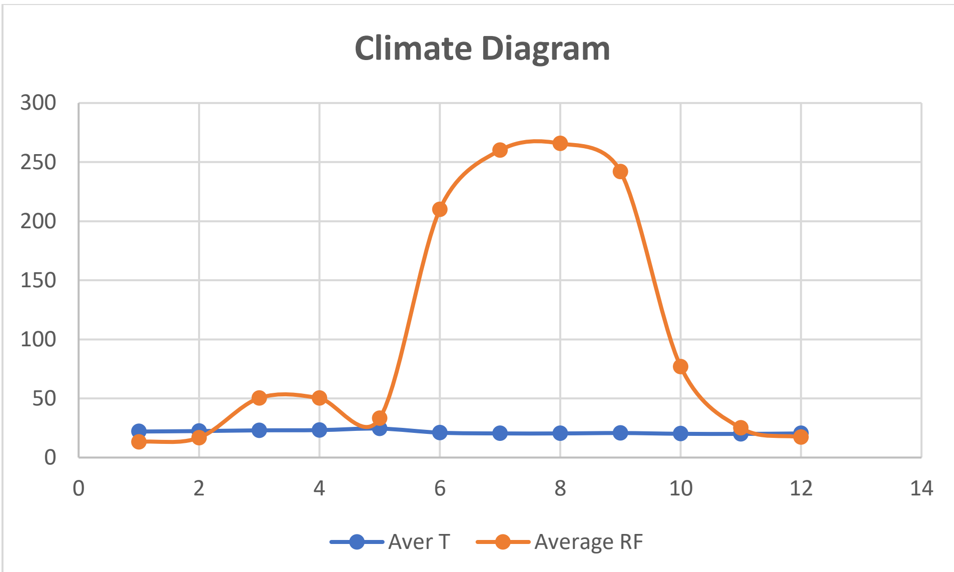


Figure 3. Rainfall and Temperature

3.1.3. Soil and geology

The Upper Awash River Basin exhibits complex geological and soil characteristics shaped by its unique topography, climatic conditions, and human activities. This basin is primarily characterized by highland escarpments, which significantly impact the hydrology & LULC. The Upper Awash River Basin in Ethiopia features diverse soil types, including Vertisols, Nitisols, Luvisols, and Cambisols. These soils are characterized by varying textures and drainage capabilities, which significantly affect agricultural productivity (Deressa et al., 2018; Tolera et al., 2023). A variety of sedimentary and volcanic strata define the study area's geology. The highlands predominantly consist of igneous rocks, primarily basalts, which are essential for soil fertility due to their mineral content (Ali et al., 2024).

3.1.4. Hydrology

The Awash River Basin in Ethiopia is indeed a vital hydrological region, particularly the Upper Awash Basin, which spans from the Chilimo Forest to the Mengesha Suba Forest (figure 4). This basin is characterized by a bimodal rainfall distribution and hydrological dynamics influenced by climate variability, LULC changes, and the management practices of water. The basin relies on multiple water sources, including rivers, streams, and underground aquifers, which are essential for meeting local communities' drinking and irrigation needs (Emiru et al., 2022). The potential for irrigation development is significant in this area, with studies indicating that proper management could enhance agricultural productivity while ensuring sustainable water use. However, LULC alterations and the change in climate variables contribute to the complexity of hydrological dynamics, affecting surface & groundwater resources (Emiru et al., 2022; Malede et al., 2024).

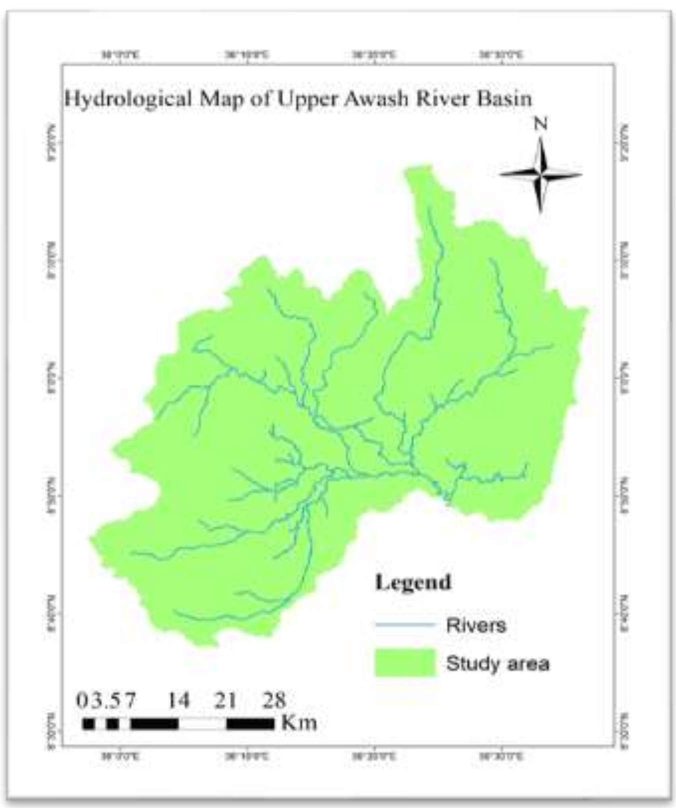


Figure 4. Hydrological Map of Upper Awash River Basin

3.1.5. Vegetation

The Upper Awash Basin predominantly features Ethiopian montane forests at higher altitudes (Chilimo and Menegasha Forests), transitioning to shrubland and wetland at lower elevations. The second most significant LULC in the basin is shrubland, which is essential to the local ecology and may support livestock grazing and other agricultural activities. The integration of woody species within agricultural landscapes is significant in the area. Upper Awash Basin is characterized by diverse tree species. The dominant tree species include *Juniperus procera, Podocarpus falcatus, Allophylus abyssinicus, Olea africana, Olea europaea, Olinia rochetiana, Rhus glutinosa,* and *Scolopia theifolia*, which are useful for biodiversity and ecosystem services in the highlands of Ethiopia (Teshome et al., 2022). The vegetation in the area not only supports local biodiversity but also provides essential environmental services, namely, soil stabilization, water regulation, & habitat for wildlife. The diverse plant communities contribute to the landscape's resilience against climate variability and human impacts. However, human activities have significantly altered these ecosystems, leading to extensive agricultural development that has replaced much of the natural vegetation.

3.1.6. Socio-economic settings

3.1.6.1 Population

The upper Awash basin plays a crucial role in Ethiopia's agricultural landscape, supporting a significant population and contributing notably to the country's agricultural output. The area's importance as a farming-related economic and demographic center is highlighted by the 1,010,525 residents projected from the central statistical agency data (CSA, 2007). Human population growth can affect water quality via increased pollution from households, industry, and agriculture. Further, LULC change associated with the growth of population can have a major impact on the basin. The population density in the upper Awash basin drives significant LULC changes characterized by urban expansion and agricultural intensification. These changes have profound implications for environmental sustainability, necessitating effective land-use policies that balance development needs with ecological preservation. The pressures of high population density lead to environmental problems, including soil degradation, deforestation, and biodiversity loss.

Intensive farming practices such as over-reliance on fertilizers and pesticides can lead to soil degradation, water contamination, nutrient depletion and biodiversity loss (Taddese et al., 2019). Furthermore, urbanization and agricultural intensification exacerbate water quality issues in the basin due to runoff from fertilizers and pesticides (Assegide et al., 2022).

3.1.6.2. Agriculture activities

The socio-economic settings of the basin are shaped by its geographical features, climatic conditions, and resource management practices. While agriculture remains a vital component of the local economy, problems such as the scarcity of water resources, land degradation, & change in climate pose significant threats to its sustainability. Agriculture is primarily concentrated in areas with gentle and flat slopes, optimizing land use for crop production. The predominant farming system integrates both crop cultivation and livestock rearing. This system allows farmers to diversify their income sources and improve their livelihoods.

Crop production

Crop production is a crucial component of the economy in the Upper Awash River Basin. The predominant crops grown in this area are cereals, which include: wheat, teff, barley, and maize. Beans, chickpeas, guava, and oil seeds are also grown but take up less space than cereals. For instance, teff is the most significant cereal crop, known for its nutritional value and economic importance. It is a staple food for many households and is often a primary source of income for farmers. Wheat is widely grown alongside teff and contributes to food security in the region. Chickpeas, lentils, and other legumes are also widely grown, with pulses important for local consumption and market sales. Farmers cultivate various vegetables such as potatoes, onions, cabbage, and fruits, although production is limited by different factors (Dafar et al., 2020). The basin's agricultural productivity is reliant on rain-fed and irrigation systems, but future water availability is a concern due to hydrologic variability (Kerim et al., 2016). The expansion of irrigation schemes and efficient water use are essential for maintaining crop yields. Additionally, the basin's agricultural activities are often affected by drought conditions, which affect the region's common crop-livestock mixed agricultural systems (Desalegn et al., 2006).

Livestock

Livestock play a significant role in basin, particularly in the context of mixed farming systems. Common livestock includes cattle, sheep, goats, and poultry. Dairy production is particularly important, providing food and income for many households. The basin's livestock sector faces challenges such as water scarcity and feed availability, which are exacerbated by environmental degradation and frequent droughts1. Livestock are often forced to travel long distances for water, highlighting the need for better water management strategies.

3.1.6.3. Urbanization

The basin is experiencing rapid urbanization, caused by the growth of population, infrastructure development, & economic growth. This region is one of the most urbanized and industrialized parts of the country, with major cities like Holeta, Sebata, Menegasha, Ginchi, and Tullu Bolo undergoing growth. The alteration of forest & cropland to built-up areas in the basin has significant impacts on the environment, ecology, and food security (Maru et al., 2023).

3.2. EVALUATION OF LULC DYNAMICS

3.2.1. Image processing and classification

The images from Landsat were made available for download on the Earth Explorer website of the USGS (https://earthexplorer.usgs.gov). Each Landsat image was geo-referenced to the WGS_84 datum and Universal Transverse Mercator Zone 37 coordinate system. The primary considerations while selecting satellite photos were the geographic, wavelength, radiometric, and historical resolutions. The images were taken in nearly the same season (between January and March) for the all-time series to ensure that they were cloud-free. They were accessed with a minimum cloud cover of ≤10%. Images with minimal cloud cover provide more reliable and comparable data across different time points, allowing for better tracking of changes over time (Rahimi & Jung, 2024). Image preprocessing was performed to improve image quality and to enhance the image for further processing or before detecting LULC changes (Cheruto et al., 2016; Vision, 1993).

The classification process and analysis of the different LULC classes were started following image preprocessing using Landsat satellite images covering Landsat 4-5, 7, and 8. Five LULC classes were established based on major ecological or land-cover types that have significant environmental implications and have significant economic activity tied to it: built-up, high forest, shrubland, wetland, and cropland (Table 1). The five chosen categories often represent significant land cover types that are crucial for environmental, ecological, and socio-economic assessments. Image processing and classification, such as radiometric correction (sun angle, atmospheric, and topographic), training sample selection and evaluation, creating and examining signature files, supervised classification, and accuracy assessment, were performed. A training sample was created for each class based on the coverage in hectares. A total of 3000 training samples were collected and evaluated for each study year (1993, 2003, 2013, and 2023). Before supervised image classification was applied, a signature file for all years was created and examined. A maximum likelihood classifier in ArcGIS 10.5 was used for supervised categorization in order to ascertain the regular distribution of the cells in each class sample in the multidimensional space. Each pixel in the data collection was compared to each interpretation key category and labelled with the name of the category it most closely resembles. These steps allowed the study to successfully classify and analyze LULC changes over time using Landsat satellite imagery, ensuring a systematic approach to understanding land cover dynamics (Alshari & Gawali, 2021; Vivekananda et al., 2021).

Table 1. The land cover classification scheme

Classes	**Description**
Built-up	The area encompasses urban and rural built-up areas such as residential, commercial, industrial areas, villages, pavement, and other infrastructure.
High forest	Areas with relatively continuous cover, both by planted and natural forests, over the land area have a crown density of greater than 20%.
Shrub-land	An area with short, sparsely growing trees and bushes with a crown density of less than 20% covers the land area.

Wetland	Areas that are partially waterlogged and swampy in the moist period & relatively drought in the dry periods are used for grazing land.
Cropland	Cultivated and uncultivated farmlands

3.2.2. Classification accuracy assessment

The precision of the classification assessment was checked using the error-matrix rule on the defined land use classes to determine how closely the results were related to the true values and to provide a qualitative collection of information from the obtained satellite data. Using GPS points, ground control points were used to validate all years of classified images. The accuracy was determined using a total of 125 ground control points. The accuracy evaluation process was carried out for all years (1993, 2003, 2013, and 2023). The overall accuracy was calculated by dividing the entire number of sample units by the sum of correctly classified sample units. To determine the overall accuracy and Kappa statistics, the following formula was used:

Overall accuracy = Number of pixels correctly classified/Total number of pixels

Kappa (Kˆ), the variation among the actual and predicted agreements, is estimated as:

$\mathbf{K}^{\wedge} = \boldsymbol{Po} - \boldsymbol{Pe}/\mathbf{1} - \boldsymbol{Pe}$

where Po = proportion of correctly classified pixels determined by the diagonal in the error matrix;

Pe = proportion of correctly classified pixels expected by chance and incorporates off-diagonal/expected classification accuracy.

These metrics are essential for assessing the accuracy and reliability of pixel-based classification models, providing insights into how well the model performs in accurately classifying image pixels (McHugh, 2012).

3.2.3. Change detection analysis

The pattern of LULC changes for each class was computed in terms of square kilometers (km^2), and the shifts in area coverage of each LULC type was computed across the time series, i.e., the classified images were compared in four periods, namely, 1993-2003, 2003-2013, 2013-2023, and 1993-2023. The shift in area coverage to every LULC type was calculated using the following formula, and the values were both percentages and hectares.

$$\text{LULC change(ha/year)} = \left(\left(\text{Area}_{(\text{final year})} - \text{Area}_{(\text{initial year})}\right)/(\text{Time interval})\right)$$

$$\% \text{ LULC change} = \left(\left(\text{Area}_{(\text{finalyear})} - \text{Area}_{(\text{initialyear})}\right)/\text{Area}_{(\text{initialyear})}\right) \times 100$$

where Area = the extent of each LULC category

% of LULC = percentage of a land use type's area that changed between the beginning and the end;

Area initial = the area of land used at the initial time;

Time interval is the amount of time between the final and starting years, and area final is the area of the same LULC type at the end.

3.2.4. Exploring the drivers of land use and land cover change

Both primary & secondary data were employed in this investigation. A semi-structured questionnaire collected information on the local community's perceptions about the drivers of LULC changes. A multistage selection procedure was used to choose the study sample households. Surveys of households, interviews with key informants, and focus group discussions were carried out to collect primary data and determine the possible major driving factors of LULC change in the study area. 210 households from the Dendi, Ejere, Wolmera, Sebata Hawas, Tulu Bolo/Becho, and Dawo woredas were selected via systematic random sampling for this study. Twelve key informants and ten individuals for focus group discussions per district were selected based on their in-depth knowledge or experience relevant to the problems in the basin (LULC changes drivers) and their ability to provide valuable insights into the research topic. This can include community representatives, kebele leaders, youth, development agents, or individuals with unique experiences pertinent to the study. The data collected from the sample were coded, organized using Excel, and analyzed using descriptive statistics.

3.3. CARBON STOCK ESTIMATION FOR EACH LULC CLASS

3.3.1. Sampling and data collection methods

A stratified systematic sampling design and rectangular plots of 10 m by 20 m were established depending on the size of each LULC type, and a systematically selected homogeneous and representative LULC type within the study area was used. A total of 260, 125, 50, and 63 sample plots for cropland, forest, shrubland, and wetland, respectively, were adopted to assess carbon stocks and environmental parameters. The size of the sample plots varied depending on the area of land use and land cover (Figure 5). Trees and shrubs with DBH ≥ 5 cm were recorded within the main plots of 200 m^2 for forest and shrubland. Soil samples were collected for four land uses (forest, shrubland, cropland, and wetland) from subplots of 1 m^2 within the main plots. The DBH at 1.3 m was measured using diameter tape, while height was measured using a Sunnto clinometer and visual estimation. The geographical coordinates of the plots and altitudes were measured using a Garmin eTrex 10 GPS receiver.

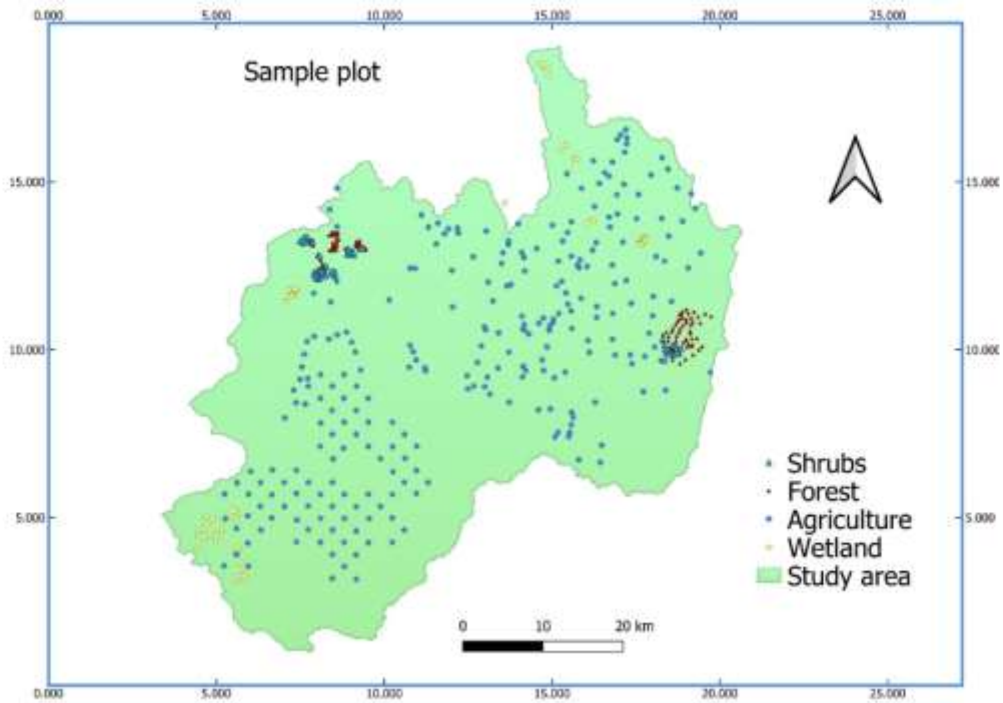


Figure 5. Geographic distribution of sample plots in the study area

Above ground biomass (AGB): The diameter (DBH) and total height of individual trees and shrubs with a DBH ≥5 cm were measured in every 200 m^2 sample plot. The AGB of trees and shrubs existing in the forest and shrubland was calculated using the general allometric model of Chave et al. (2014), as stated below. The equation uses DBH and height measured from the sampling plots, as well as the wood density values taken from the global wood density database.

$$\mathbf{Y = 0.0559\ (\rho D^2 H)}$$

where Y is the predicted aboveground total biomass (kg), D is the measurement of the diameter at DBH, H is the height, and ρ is the wood density (g/cm^3) from the global wood density database. The carbon stock was considered to be 47% of the AGB carbon stock (Terakunpisut et al., 2007).

Above Ground Carbon (AGC) = Above Ground Biomass × 0.47

Belowground Biomass (BGB): The measurement of belowground biomass is more difficult and time-consuming than AGB measurement. Consequently, it was calculated by MacDicken (1997) that this value is 20% of the AGB.

Below Ground Carbon (BGC) = Below Ground Biomass × 0.47

Soil organic carbon (SOC): The soil samples were collected from four LULC systems, and the samples were taken from five points. For SOC analysis, the soil samples were allowed to air dry before being run through a 2 mm screen. One hundred grams (100 g) of the mixed soil samples were determined in the laboratory and used for the determination of SOC. The sample was dried in the oven for 24 hours at 105°C to achieve a constant weight. The depth, bulk density, and organic carbon concentrations were used to create an accurate inventory of carbon stocks in each of the four LULC types. The quantity of soil carbon per hectare was computed as stated below (Pearson et al., 2005; IPCC, 2006; Pearson et al., 2007).

$$\boldsymbol{SOC} = \mathbf{BD} * \mathbf{d} * \%\mathbf{C}$$

where BD is the soil bulk density (g cm3), D is the total depth (30 cm), %C is the carbon concentration (%), and SOC is the soil organic carbon stock per unit area. The soil carbon concentration was calculated in the lab.

Bulk density was computed using the following equation:

$$\mathbf{BD} = \mathbf{Mav.dry}/\mathbf{Vc}$$

where BD = bulk density of soil sample (g/cm^3), Mav = average dry weight of soil sample per plot (g), and V = volume of soil sample in the core sampler (cm^3) (Pearson et al., 2005).

3.3.2. Carbon stock estimation using the InVEST model

The InVEST model, which operates simply with flexible parameters and obtains more accurate results, is mainly used to calculate the LULC dynamics affecting carbon storage

(Jiang et al., 2017). Currently, substantial research has proven the use of InVEST models in simulating and evaluating LULC change effects on the amount of carbon stored (Wei et al., 2021; Xu et al., 2020; Maanan et al., 2019). The model used land cover maps and data on stocks in three carbon pools (aboveground biomass, belowground biomass, & SOC) to estimate carbon stored in a selected area.

The carbon stock changes were estimated using the InVEST model. The model was applied to the LULC maps to calculate the cumulative shifts in carbon stocks for each LULC, assuming that any change in carbon stocks was due to changes between one LULC and another (Maanan et al., 2019). The model estimates the entire carbon stock based on the aggregated carbon pool values assigned for each LULC class (Sharp et al. 2020). Carbon storage was divided into four basic carbon pools for each LULC type: aboveground biomass (Cabove), belowground biomass (Cbelow), soil organic matter (Csoil), & the dead organic matter (Cdead) (Sharp et al., 2020), but dead organic matter was not considered for the forestland due to a lack of data. AGB mainly refers to the carbon of living vegetation on the surface, while BGB mainly refers to the carbon in the root systems of underground forests and shrublands. The soil organics mainly included organic carbon in the soil for four land uses (forest, shrub, crop, and wetland).

The LULC data and carbon pools served as inputs to estimate carbon stocks for each grid cell and the entire basin. The spatial distribution of carbon stored in the terrestrial ecosytem is estimated by combining LULC data and corresponding carbon pool data (Figure 6). The three decades of carbon preservation were determined from the LULC maps of 1993, 2003, 2013, and 2023. The InVEST model was used to assess the impact of LULC changes over a study period, using a CSV table with fundamental carbon pools and lucode data. The carbon density/stock (Ck) for LULC type i is equal to the sum of the aboveground, belowground, and soil carbon densities for LULC type i.

Ck = Cabove + Cbelow + Csoil, where Ck = total amount of carbon

The total Upper Awash River Basin carbon storage (Ct) is equal to the sum of carbon density for LULC type i multiplied by the area (Aqi) for LULC type i, with n as the number of LULC types, which is set to 4 in this study (Figure 6).

$$Ct = \sum_{n}^{i} (CABgi * Aqi) + (CBgi * Aqi) + (CSi * Aqi)$$

The mean value of carbon kept above ground within the land use I is denoted by CABgi, the mean amount of carbon stored below ground with land use I is denoted by CBgi, and the average amount of carbon stored in soil with LULC is denoted by CSi. Aqi is the area of a particular kind of LULC.

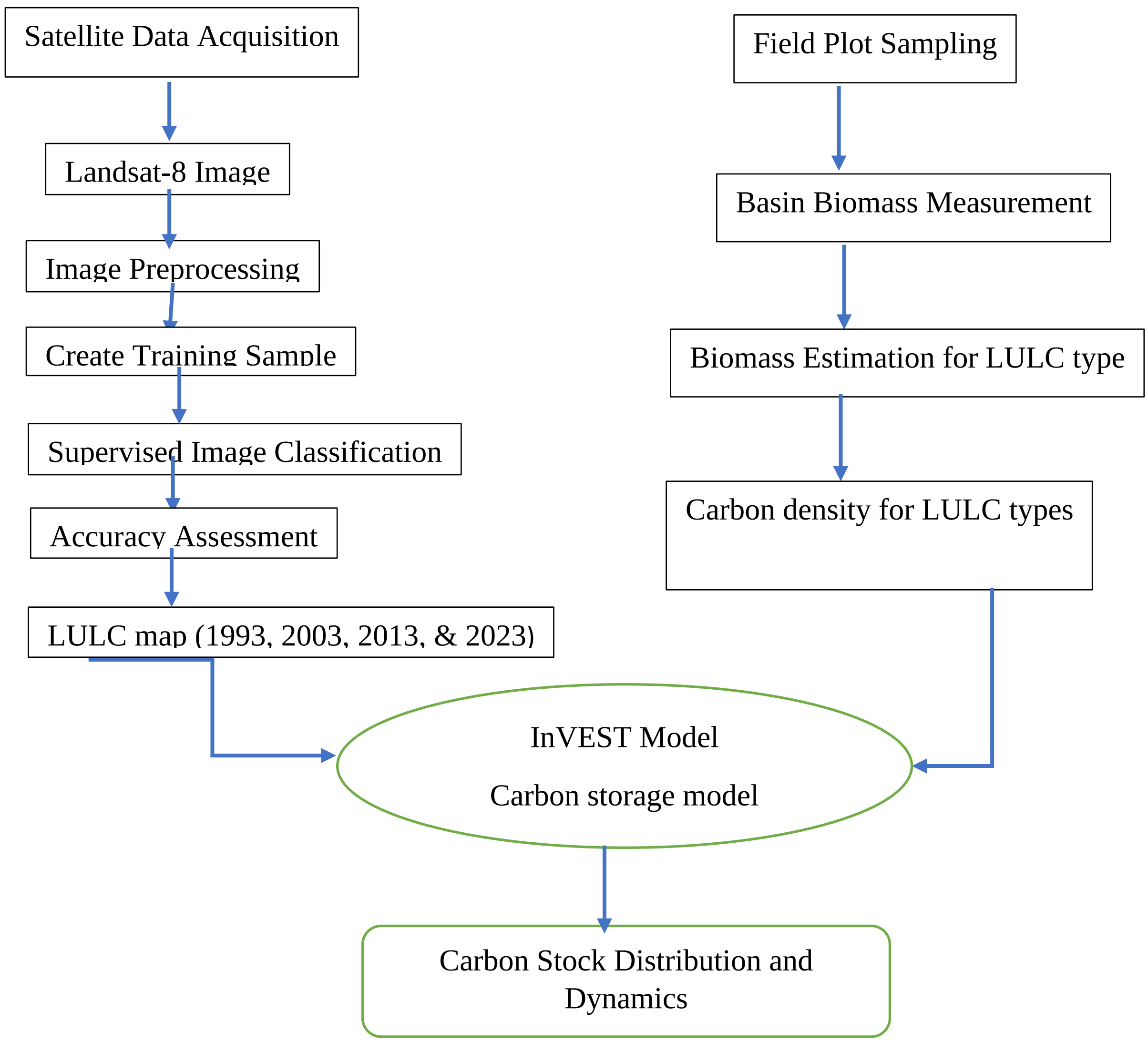


Figure 6. Method of carbon stock dynamic assessment

3.4. ECOSYSTEM SERVICE VALUE ESTIMATION

The shifts in ecosystem service valuation were calculated using classified LULC data from 1993, 2003, 2013, & 2023. This study used the coefficients from Costanza et al. (2014) for

16 biomes to estimate ESVs for the five LULC categories. The LULC types of the basin were assigned to appropriate representative biomes (Table 2). Adjustments were made to associate the study area's LULC types with the closest equivalent biomes (Costanza et al., 2014). Similar methods have been used in other studies (Kreuter et al., 2001; Tolessa et al., 2018; Kindu et al., 2016; Woldeyohannes et al., 2020). The ESV for each LULC category and the overall ESV for the basin were computed using the assessment model that Costanza et al., (1997) had predicted. The values of 17 specific ecosystem functions were also estimated using modified coefficients (Table 3).

$$ESV_k = \sum(A_k * VC_k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$ESV_f = \sum(A_k * VC_{fk}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

where AK is an area of LULC type 'k', VCk is the value variable of LULC type 'k', & VCf k is the value variable of function 'f' for LULC type 'k. The ESV service function (f) and the ESVs of LULC type (k) are represented by ESVk and ESVf, respectively.

The percent change in ESV across different periods (1993-2003, 2003-2013, 2013-2023, 1993-2023) was calculated using Eq. (3) based on the assessment model suggested by Costanza et al. (1997) & considering previous studies by Kreuter et al. (2001), Tolessa et al. (2018), Kindu et al. (2016), and Woldeyohannes et al. (2020). The percent change in ESV over different periods (1993-2003, 2003-2013, 2013-2023, 1993-2023) was calculated using Eq. (3), which depends on the assessment model advised by Costanza et al. (1997) and takes into account previous studies by Kreuter et al., (2001), Tolessa et al., (2018), Kindu et al., (2016), & Woldeyohannes et al. (2020). The shifts in the ESV were computed by subtracting the assessed values from every data point and comparing the results from a single dataset to the corresponding values of the next dataset in each time frame. The findings are displayed in a brief table of the overall changes in ESV as US dollars and percentages.

$$Percent\ of\ ESV\ change = \left(\frac{ESV_{recent\ year} - ESV_{intial\ year}}{ESV_{intial\ year}}\right) * 100 \ldots\ldots\ldots\ldots\ldots \quad (3)$$

where ESV represents the entire estimated value of environmental services.

Table 2. LULC categories, equivalent biomes, and ESV coefficients derived from Costanza et al., (2014)

LULC categories	Equivalent biome	Ecosystem service coefficient ((2007 US $ ha^{-1} yr^{-1})
Cropland	Cropland	5568
Forest	Tropical Forest	5381
Shrubland	Tropical Forest	5381
Wetland	Swamps/floodplains	25,681
Built-up area	Urban	6661

Table 3. ESV coefficients of equivalent biomes (2007 USD ha^{-1} year^{-1}) for the LULC classifications (Costanza et al., 2014)

	Biome			
Ecosystem service	**Cropland**	**Tropical forest**	**Swamps/floodplains**	**Urban**
Provisioning-services				
Food-production	2323	200	614	
Water-supply	400	27	408	
Raw-materials	219	84	539	
Genetic-resources	1042	1527	99	
Regulation-services				
Water-regulation	-	8	5606	16
Waste-treatment	397	120	3015	
Erosion-control	107	337	2607	
Climate-regulation	411	2044	488	905
Biological-control	33	11	948	
Gas-regulation		12		
Disturbance-regulation		66	2986	
Supporting-services				
Nutrient-cycling		3	1713	
Pollination	22	30		
Soil-formation	532	14		
Habitat/refuge		39	2455	
Cultural-services				
Recreation	82	867	2211	5740
Cultural		2	1992	
Sum	**5568**	**5381**	**25681**	**6661**

3.4.1. Coefficient of sensitivity

Sensitivity analyses were performed using standard economic methods to account for the imprecise matches between the biome values provided and the identified land use. The value coefficients were modified by ±50% by applying the economic notion of elasticity (Kreuter et al., 2001; X. Li et al., 2022; Y. C. Li & He, 2008; S. Li et al., 2022; Hu et al., 2008). The computed ESV is elastic if the corresponding coefficient of sensitivity is greater than one; the value is inelastic if the corresponding coefficient of sensitivity is less than one. An inelastic estimated ESV for the value coefficient indicates a reliable proxy representation. Sensitivity analysis has been frequently used in previous studies to determine the effect of deviations in the value coefficient on the ESV (Chuai et al., 2016; Gashaw et al., 2018; Wang et al., 2020; Yuan et al., 2019).

$$CS = \frac{\frac{ESV_j - ESV_i}{ESV_i}}{\frac{\left(VC_{jk-} VC_{ik}\right)}{VC_{ik}}}$$

where VC_{ik} and VC_{jk} are the initial and modified value coefficients (US\$ ha^{-1} year^{-1}) for LULC type k, respectively, and the coefficient of sensitivity is represented by CS. The initial and modified entire estimated ESV of all ESs are expressed as ESV_i and ESV_j, respectively (in monetary units per year).

3.5. VEGETATION INDICES (VI) MAPPING AND EXTRACTION

Spectral modifications in data from remote sensing, known as vegetation indices, improve vegetation features and allow precise historical and regional comparisons of changes in structure of the canopy and biomass on the ground (Huete, 1999, Didan et al., 2018, Taddese et al., 2020). Satellite-derived vegetation indices provide radiometric assessments of quantity, circumstances, organization, as well as seasonal and interannual changes, making them crucial for tracking, visualization, and organizing terrestrial vegetation (Isbaex et al., 2021; Isbaex & Margarida Coelho, 2021).

The vegetation indices were derived from satellite datasets (Landsat 8) to assess the density and health of vegetation, which is essential for monitoring the amount of carbon stored in the basin. The extracted spectral bands were used to calculate various vegetation indices in

Arc ArcGIS software. This process involves combining the pixel values from two or more spectral bands in a multispectral image to highlight specific phenomena such as vegetation, water, snow, or soil. The calculated vegetation indices were used to create maps that provide information for monitoring different aspects of vegetation. The values were exported in CSV format data formats for correlation & regression analysis in an Excel sheet, and the field of the plot's spatial location points was utilized as landmarks to match the pixels.

3.5.1. Normalized difference vegetation index (NDVI)

To obtain the pixel values associated with biomass/carbon, the NDVI equation was used. The NDVI is one of the standardized indices that use the combination of the red (0.62–0.68 μm) reflectance and near-infrared (0.75–0.89 μm) reflectance of the electromagnetic spectrum and is defined as:

NDVI is equal to (NIR-R)/(NIR+R).

where R is the red band & NIR is the near-infrared band. The NDVI map is a greyscale raster map with index values between +1 &−1. An extremely negative value refers to the water content; values closer to zero refer to bare land, and the highest values represent green vegetation(Mei et al., 2016; Tan et al., 2015).

3.5.2. Enhanced vegetation index (EVI)

To compare the index distribution values for the research area, the EVI index equation was utilized (Huete, 1999):

EVI is equal to 2.5 * ((NIR - RED) / (NIR + C1 * RED - C2 * BLUE + L)), where NIR stands for near infrared band, RED for red band, BLUE for blue band, L: value to correct for canopy background (0, 0.5 & 1), C1: values as constants for atmospheric confrontation: Value 6, and C2: values as constants for atmospheric confrontation: Value 7.5.

3.5.3. Soil-adjusted vegetation index (SAVI)

Vegetation indices can be obtained from satellite data, which is a primary source of information for monitoring and assessing the vegetation cover of an area (Gilabert et al., 2002). However, soil background conditions have a substantial impact on partial canopy spectra and the calculated vegetation indices (Huete, 1999). This can be controlled by applying the following formula, which involves the addition of a constant, L, to the denominator of the NDVI equation:

SAVI is equal to ((NIR-R)⁄(NIR+R+L) *(1+L))

3.5.4. Correlation between the field carbon stock value with vegetation indices

Based on calculations of the carbon stocks estimation of the modeled correlation between carbon stocks and the value of NDVI, SAVI, and EVI was carried out. The correlations were calculated by the linear regression equation: **y = a + bx.** the values of a and b can be calculated using the following formula (Pandapotan Situmorang et al., 2016; Walpole. 1992):

$$\boldsymbol{b = \frac{\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^{\,2}}}$$

$$\boldsymbol{a = \frac{\sum_{i=1}^{n} y_i}{n} - b\frac{\sum_{i}^{n} x_i}{n}}$$

x = NDVI/EVI/SAVI value

y = Carbon value

The correlation coefficient (R or r), also known as the product-moment correlation coefficient or Pearson's correlation coefficient, measures the linear relationship between two variables, x, and y, while the coefficient of determination (R^2 or r^2) measures the proportion of variance in regression explained by explanatory variables, indicating the strength of the relationship between variables (Kasuya, 2019). The correlation analysis is calculated using the following Pearson correlation test equation:

$$\boldsymbol{r = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{\sqrt{[n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^{\,2}][n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} xy_i)^{\,2}]}}}$$

r = Coefficient of correlation

n = Number of plots

x = NDVI/EVI/SAVI value

y = Carbon value

Based on the above calculation, a Pearson correlation of the carbon value with the NDVI, SAVI, and EVI was developed to estimate the entire carbon stock in the basin. The strength of a Pearson correlation coefficient can be categorized as follows: **Very Weak**: r values between 0.00 and 0.19, **Weak**: r values between 0.20 and 0.39, **Moderate:** r values between 0.40 and 0.59, **Strong**: *r* r values between 0.60 and 0.79, and **Very Strong**: r values between 0.80 and 1.0 (Samuels, 2016; Obilor & Amadi, 2018; Asuero et al., 2006).

3.5.5. Total carbon stock estimation

The NDVI, SAVI, and EVI values from the Landsat 8 data were used to estimate landscape carbon. GPS was used to obtain the exact geographic coordinates of the sampling plots. Ground truth points were imported to generate vector data (points) in the ArcGIS environment, which was then overlaid on the NDVI, SAVI and EVI products to extract the NDVI, SAVI and EVI values (Figure 7). For statistical analysis, the extracted NDVI, SAVI and EVI values were regressed against the carbon values measured in the field. The linear equation obtained was then used to generate the area's final estimated carbon map.

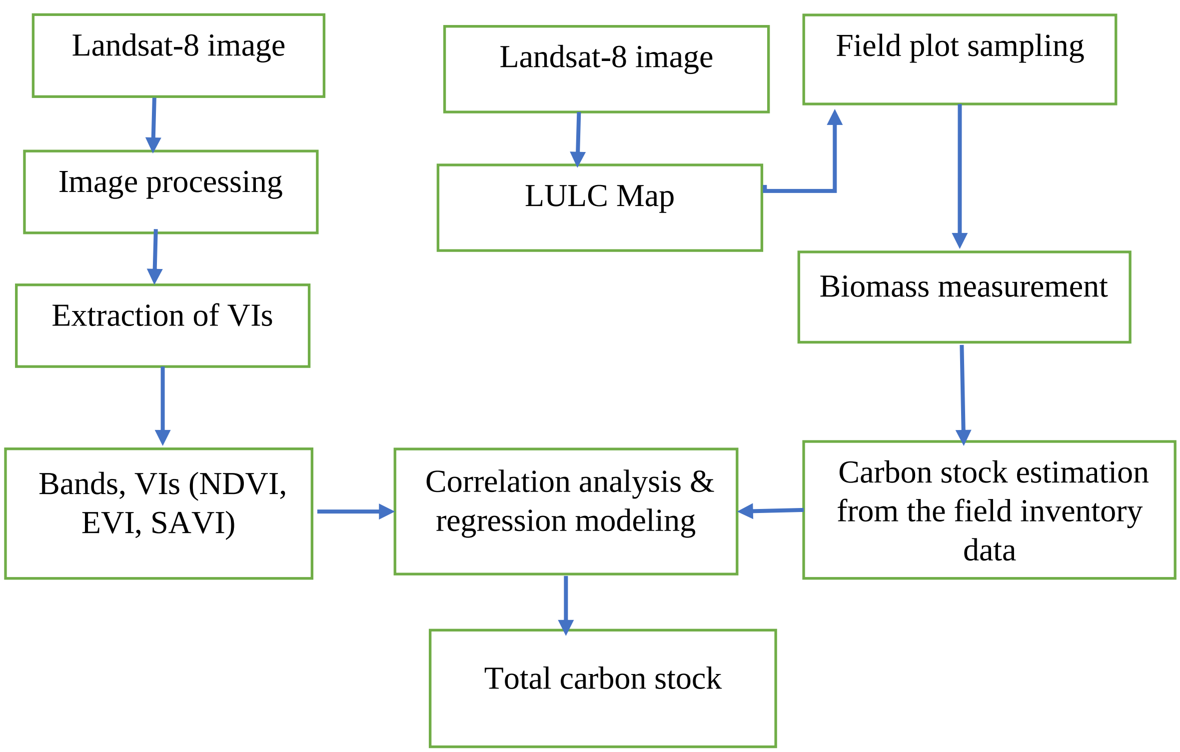


Figure 7. Total carbon stock estimation method

CHAPTER FOUR

4. RESULTS

4.1. EVALUATING LAND USE AND LAND COVER CHANGE PATTERN FROM 1993-2023

4.1.1. Classification and accuracy assessment

This data shows the producer accuracy as well as the user accuracy for different LULC classes in 1993, 2003, 2013, and 2023. The accuracy of LULC classifications was evaluated using error matrices derived from ground truth points. The accuracy for built-up areas has remained relatively stable over the years, with both user accuracy (UA) and producer accuracy (PA) around 86.67% in 2023. The accuracy for forestland has been high, with PA reaching 100% in 2003 and 2023, indicating perfect classification for those years. The accuracy for shrubland, wetlands, and cropland improved over time, with UA reaching 92%, 96%, and 92.5%, respectively, in 2023. The results showed that for certain land cover types, such as shrubland, wetlands, and cropland, there is a clear improvement in accuracy over time. Built-up areas and forestland have shown stable or consistently high accuracy. These types of land cover may be easier to classify because they tend to have stable features that are easy to detect and distinguish, and they don't change as dramatically over time as other land types like cropland or wetlands.

The results presented the performance of supervised LULC classification for four different years (1993, 2003, 2013, and 2023) in a study area. These results include two important metrics commonly used to evaluate classification accuracy: the Kappa coefficient and overall accuracy. The Kappa coefficient measures the agreement between the classification results & data from the ground truth, taking into account the likelihood of random agreement, whereas the overall accuracy reflects the percentage of pixels correctly classified in the dataset compared to the entire extent of pixels. The supervised LULC classifications for 1993, 2003, 2013, and 2023 showed high overall classification accuracy and Kappa values, enabling the detection of changing scenarios in the study basin. Kappa coefficients were 77.5%, 82.7%, 84%, and 87.6%, while overall accuracies were 85.6%, 88.8%, 89.6%, and 92% for the respective years (Table 4). These results demonstrate a significant relationship between the identified LULC changes & ground control point data. The overall accuracy has consistently improved from 85.6% in 1993 to 92% in 2023, and the Kappa coefficient has also improved, indicating better agreement between the classified data and the actual land cover over time, reaching 87.6% in 2023. This data suggests that the classification methods have become more accurate and reliable over the years, leading to better land cover mapping.

Table 4. Summary of accuracy assessments of LULC classification (1993-2023)

Class Name	**1993**		**2003**		**2013**		**2023**	
	UA (%)	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**	**PA (%)**	**UA (%)**	**PA (%)**
Built-up	80	85.7	80	85.7	86.7	86.67	86.67	86.67
Forestland	85	94.4	90	100	90	94.74	90.00	100
Shrub-land	84	80.8	88	88	88	88	92.00	88.5
Wetland	88	84.6	92	88.5	92	92	96.00	88.9
Cropland	87.5	85.4	90	85.7	90	87.8	92.50	90.2
Overall accuracy	85.6		88.8		89.6		92	
Kappa coefficient	77.5		82.7		84		87.6	

Note: PA stands for producer accuracy, and UA for user accuracy.

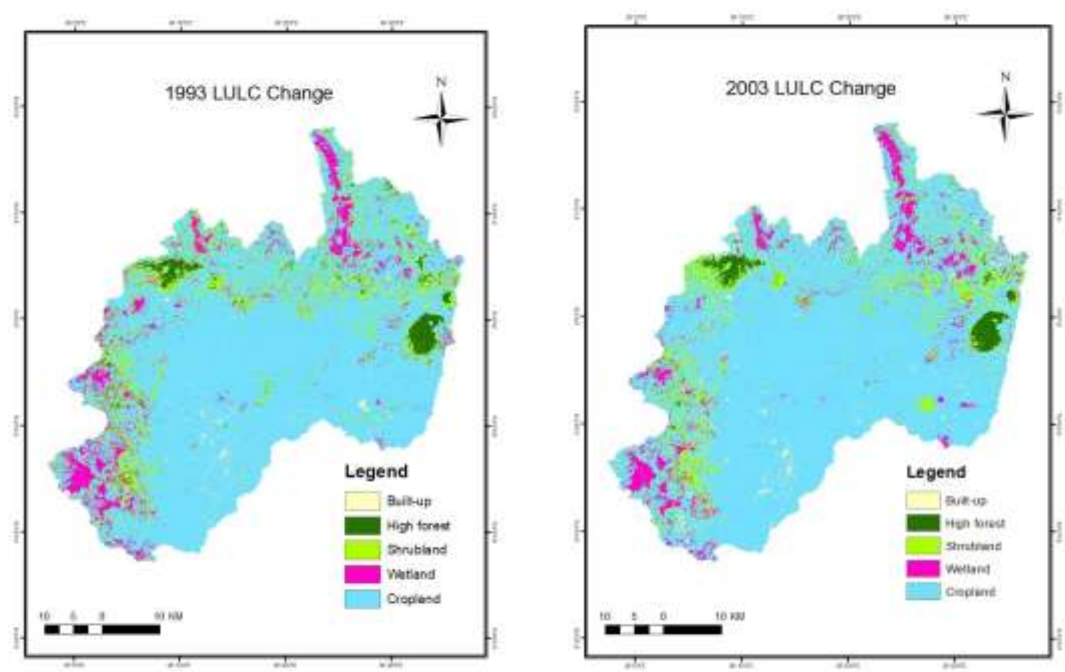
4.1.2. Land use and land cover maps

The LULC maps for 1993, 2003, 2013, and 2023 were generated from Landsat 4-5, 7, and 8 (Figure 8). In 1993, cultivated land covered 79.63% of the study area, increasing to 86.88% by 2023 due to population growth driving demand for new cultivation land and settlements, leading to the reduction of other LULC types. The increase in cropland has led to a corresponding decrease in other LULC types, namely forests & wetlands. Forest coverage decreased from 2.58% in 1993 to 1.87% in 2023 (Table 5), likely due to deforestation for agricultural expansion. Over the past 30 years, cultivated land increased by approximately 9%, while forestland decreased by 27% from its 1993 coverage (Tables 5 and 6).

There has been a steady increase in the built-up area over the last 30 years. From 1.10% of the land in 1993, built-up areas grew to 2.79% in 2023 (Table 5). This represents a loss of 2,000 ha of forested land. This reflects urbanization or the expansion of infrastructure, such as residential, commercial, and industrial developments. The data illustrate a clear trend of increasing urbanization & cropland use at the cost of forests and wetland landscapes over the past three decades. These changes might have significant implications for biodiversity conservation & environmental services in the region.

Table 5. LULC map over time (areas in ha and %)

Class	1993		2003		2013		2023	
Name	**Ha**	**%**	**Ha**	**%**	**Ha**	**%**	**Ha**	**%**
Built-up	3,100	1.10	4,800	1.70	6,900	2.44	7,900	2.79
Forestland	7,300	2.58	6,400	2.26	5,800	2.05	5,300	1.87
Shrubland	27,900	9.87	24,100	8.52	16,400	5.80	16,300	5.77
Wetland	19,300	6.83	16,900	5.98	14,400	5.09	7,600	2.69
Cropland	225,100	79.63	230,500	81.54	239,200	84.61	245,600	86.88
Total	**282,700**	**100**	**282,700**	**100**	**282,700**	**100**	**282,700**	**100**



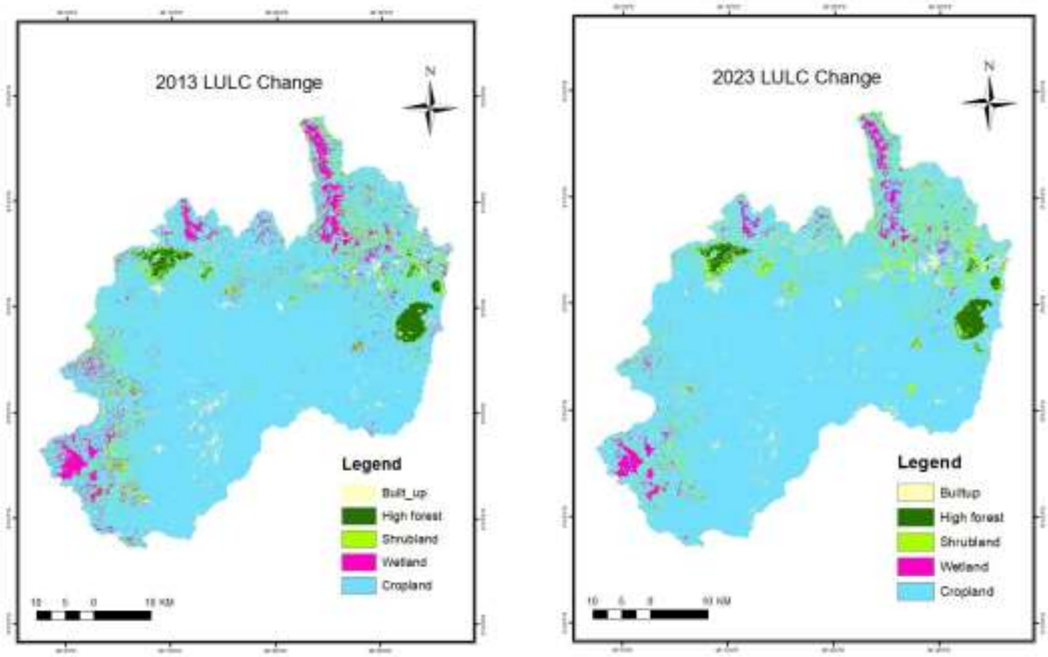


Figure 8. Land use land cover maps (1993, 2003, 2013, and 2023)

4.1.3. Land use and land cover change

Table 6 summarizes significant land use category changes over three periods: 1993–2003, 2003–2013, and 2013–2023. The overall trends indicate a complex interplay between urban development, agricultural practices, and ecological changes. Results showed a continuous decline in forests, shrubs, and wetlands, & a rise in cropland & built-up areas (Figure 9). There has been a significant rise in built-up areas across all periods, culminating in a total increase of 4,800 hectares, representing a 154.84% rise from the baseline in 1993. This suggests urbanization or expansion of infrastructure, with the area dedicated to buildings, roads, industry, and other human activities growing rapidly. In contrast to built-up areas, high forest cover has seen a significant decline over the years, with a total loss of 2,000 hectares, reflecting a 27.40% decrease. This could indicate deforestation or land being cleared for other uses, such as agriculture or settlement. The decrease was steady over the three time periods (1993-2003, 2003-2013, and 2013-2023), with losses each decade.

Shrubland has also experienced a dramatic reduction of 11,600 hectares, indicating a 41.58% decrease over the three decades. This is a significant loss, and it might reflect land conversion to agriculture or urban use in which a more drastic decline of 7,700 Ha (-

31.95%) occurred between 2003-2013, and a minor reduction of 100 ha (-0.61%) occurred between 2013-2023. The loss of wetland areas is particularly alarming, with a total decrease of 11,700 hectares, which translates to a 60.62% reduction while agricultural lands increased by 2.4%, 3.77%, and 2.68% in the 1st, 2nd & 3rd periods, correspondingly (Table 6). The drop in wetland area seems to have been especially steep after 2013, with a loss of 6,800 hectares (-47.22%) in that period alone. Cropland grew by 20,500 hectares (+9.11%), especially noticeable in the second period (2003-2013), where there was a substantial increase of 8,700 hectares. This indicates expansion in agricultural production, possibly due to increasing demand for food.

Table 6. Trends of LULC changes in different periods

Class Name	1993-2003		2003-2013		2013-2023		1993-2023	
	Ha	%	Ha	%	Ha	%	Ha	%
Built-up	1,700	54.84	2,100	43.75	1000	14.49	4,800	154.84
High forest	-900	-12.33	-600	-9.38	-500	-8.62	-2,000	-27.40
Shrub-land	-3,800	-13.62	-7,700	-31.95	-100	-0.61	-11,600	-41.58
Wetland	-2,400	-12.44	-2,500	-14.79	-6,800	-47.22	-11,700	-60.62
Cropland	5,400	2.40	8,700	3.77	64	2.68	20,500	9.11

A basin has experienced significant LULC changes over the past thirty years. This analysis emphasizes the transformations observed between 1993 and 2023, highlighting the rapid decline of natural habitats and the corresponding increase in cropland and built-up areas. The high forest area decreased from 7,300 hectares in 1993 to 5,300 hectares by 2023. Over the same period, the area of shrubland decreased from 27,900 hectares to 16,300 hectares. Additionally, the wetland area decreased from 19,300 hectares to 7,600 hectares. These reductions are attributed to the shifts of wetland into cropland and urban developments. The overall loss of these natural habitats is indicative of a broader trend where approximately 50,600 hectares (17.9%) of the total land area changed, while 232,100 hectares (82.1%) remained unchanged out of a total of 282,700 hectares assessed since 1993.

The overall trend from 1993 to 2023 shows a significant conversion of natural land (forestland, shrubland, and wetlands) into agricultural land (cropland) and urban areas (built-up). This imitates larger global trends in LULC, where urbanization & agricultural expansion often come at the cost of terrestrial ecosystems. The significant decline in high forest, shrubland, & wetland areas suggests that natural landscapes are being replaced or degraded, which could have consequences for biodiversity, carbon sequestration, and ecosystem services. The increase in cropland shows the rising demand for crop production, possibly linked to the growth of population or shifts in farming practices. The pattern suggests significant land-use change driven by urbanization and agriculture, with natural areas (especially wetlands and forests) being converted at a concerning rate. These trends reflect broader environmental changes and highlight the need for sustainable land management practices to balance development with conservation efforts.

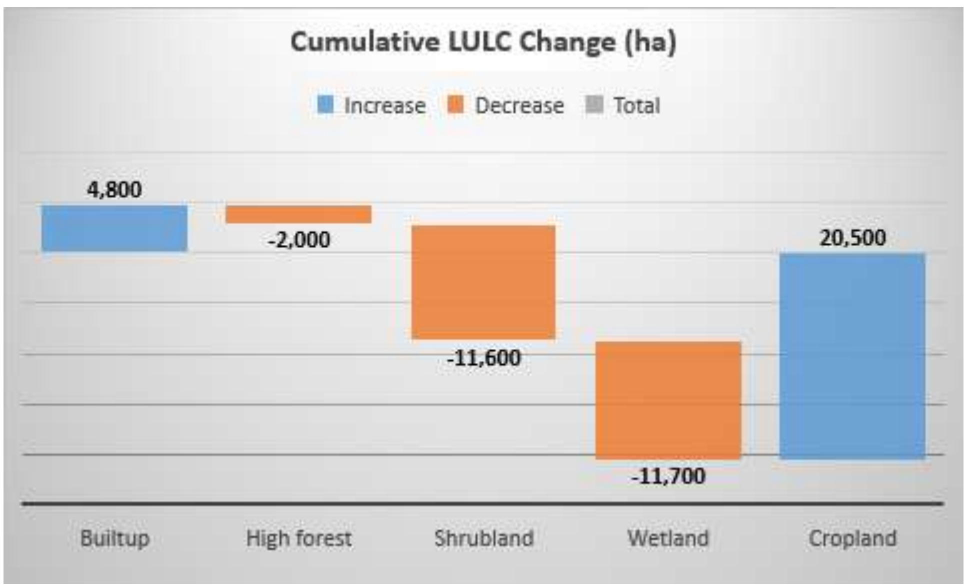


Figure 9. Total trend of land use land cover change (1993-2023)

4.1.4. Drivers of land use and land cover change

LULC changes in the Upper Awash River Basin, like in many regions of Ethiopia, are mainly driven by anthropogenic (human-driven) factors. Table 7 below presents the perceptions of various drivers of LULC changes among a surveyed population. The responses are categorized into three groups: Agree, Undecided, and Disagree. Based on the provided statistics, here's a detailed analysis of each driver.

The results showed that agricultural expansion and population pressure are key drivers of LULC changes. Agricultural expansion is overwhelmingly recognized as a primary driver of LULC change, indicating a strong consensus on its impact on land use dynamics. Agricultural expansion was identified by 89.52% of respondents as a primary driver of LULC changes (Figure 10, Table 7). Many respondents agreed that the expansion of agriculture is a key driver of LULC changes. This trend is largely attributed to the food demands, which lead to the conversion of forestland into agricultural fields. The region's favourable climate and fertile soil have made it an attractive area for cropland development. While this expansion can support food security and economic growth, it can also lead to significant environmental costs, namely deforestation, biodiversity loss, and degradation of soil. The conversion of forests or natural landscapes to farmland also disrupts the ecosystem services of the Upper Awash River Basin.

The perception of population pressure as a driver suggests that increasing human populations are influencing land use decisions, likely leading to more agricultural and urban development. The increasing human population was a major underlying cause of agricultural land expansion and overexploitation of natural resources. Population pressure was noted by 87.14% of respondents as a major underlying cause of land use changes (Figure 10, Table 7). A basin experiencing significant changes in LULC due to the rapid growth of population & urbanization. As the number of the population rises, there is an increasing need for land for housing, infrastructure, and services, leading to the expansion of urban areas at the cost of agricultural lands, forests, shrublands, and wetlands. As more land is converted for agriculture and settlements, there are significant implications for biodiversity and ecosystem services, as natural habitats result in reduced long-term sustainability and increased vulnerability to environmental shocks, like droughts or soil erosion. For instance, agricultural lands, which are vital for food production, are being replaced by new developments, and this expansion is also encroaching on important ecosystems like forests, shrublands, and wetlands. These ecosystems provide essential services, such as biodiversity support and water regulation, and their loss can lead to environmental degradation.

The results also showed that the demand for timber, fuelwood, and charcoal production contributes to deforestation, leading to the loss of natural forests and biodiversity. Wood extraction, especially for timber and fuelwood, is also seen as a significant driver by most people. Wood extraction for fuel wood, charcoal, and construction materials was another major driver, with 85.71% of respondents suggesting it as the most prevalent cause of vegetation destruction. For many of the basin's communities, fuelwood and charcoal serve as their primary energy sources. Unsustainable logging practices in the area lead to the destruction of large areas of forest and shrubland, disrupting ecosystems.

High percentages (84.29%) believe that urban and infrastructure expansion contributes to LULC changes. As cities grow, natural land (such as forests, wetlands, or agricultural land) is often converted into residential, commercial, or industrial areas. While over 70% agree that poverty is a driver of LULC changes, there is a notable portion (10.95%) that disagrees. Poverty often drives people to exploit land resources unsustainably, as poor communities might rely heavily on agriculture, timber extraction, or land clearing for survival.

Poor land tenure systems and unclear user rights have been cited as underlying causes of LULC changes however, the land tenure system shows the least consensus among the drivers listed, indicating that opinions on its impact on LULC changes are quite divided. The existing land tenure system was identified by 52.38% of respondents as an indirect factor influencing LULC changes, suggesting that policies related to land ownership may affect agricultural practices and resource use (Table 7).

Table 7. Drivers of LULC change

Drivers of LULC changes	**Perception about LULC Drivers**					
	Agree		**Undecided**		**Disagree**	
	No	**%**	**No**	**%**	**No**	**%**
Agricultural expansions	188	89.52	15	7.14	7	3.33
Wood extraction	180	85.71	20	9.52	10	4.76
Population pressure	183	87.14	21	10.0	6	2.86

Urban and infrastructure expansion	177	84.29	26	12.4	7	3.33
Poverty	150	71.43	37	17.6	23	10.95
Land tenure system	110	52.38	54	25.7	46	21.90

Total number of respondents = 210

Figure 10 below shows a structured flowchart detailing the drivers of LULC change. It categorized these drivers into direct and indirect factors. The direct drivers focus on human activities like deforestation, infrastructure development, and agricultural expansion that directly alter LULC. The indirect drivers highlight the underlying socioeconomic and governance-related issues such as poverty and weak land tenure systems push communities to exploit land unsustainably.

The results showed that the unwise use of natural resources for construction materials, charcoal, fuel wood consumption, overgrazing, and inappropriate agricultural practices has led to the removal of natural vegetation cover and wetland shrinkage in the upper Awash basin (Figure 10). Overgrazing by increasing livestock populations in forest areas has also led to forest degradation and negatively impacted regeneration. Poor tenure systems and unclear user rights for forests and wetlands are other underlying causes of LULC changes (Figure 10). In general, the results indicates that agricultural expansion, wood extraction, population pressure, and urbanization are widely recognized as key drivers of LULC shifts by the surveyed population. In contrast, perceptions regarding poverty and land tenure systems are more varied, suggesting that these factors may influence land use dynamics differently across contexts or communities.

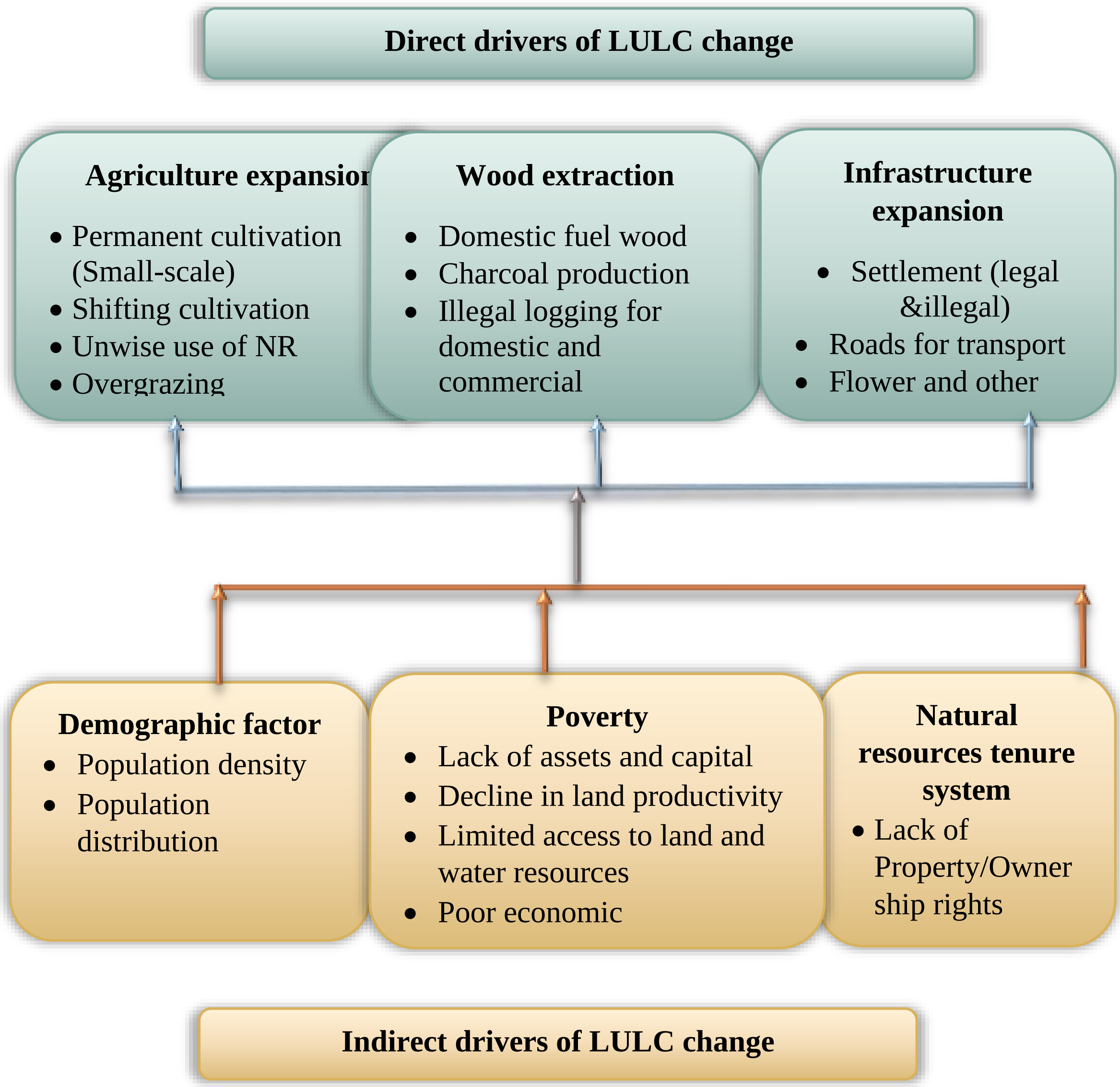


Figure 10. Direct and indirect drivers of LULC change

4.2. LANDSCAPE CARBON STOCK AND DYNAMICS

4.2.1. Landscape carbon stocks in different pools

Table 8 provides the total carbon (t/ha) found in different LULC classes, categorized into three main components: AGC, BGC, and SOC. Forests have a high amount of total carbon, with the majority of it stored in the above-ground biomass at 125.21 t/ha. The soil holds a significant amount of carbon too (108.7 t/ha), highlighting the role of SOM in carbon storage. The below-ground carbon (root systems) is lower than the above-ground carbon, but still contributes to the overall carbon pool.

Shrublands store less total carbon than forests, with 169.21 t/ha of carbon overall. While the above-ground carbon is lower than in forests (53.056 t/ha), the soil organic carbon is relatively high (105.541 t/ha). This suggests that although shrubland biomass is smaller than forest biomass, the soil in shrublands is a significant carbon store. Below-ground carbon in shrublands (10.611 t/ha) was proportionally lower than above-ground carbon. Wetlands primarily store carbon in the soil, with no significant above-ground or below-ground biomass. Wetlands have 76.44 t/ha of total carbon, and this is all contained in the soil. Among the three carbon pools in forestland, the AGB had the highest recorded value, followed by the soil carbon stock (Table 8), whereas the SOC had the highest recorded value in shrubland, followed by the AGB. The total carbon in croplands comes solely from soil organic carbon. Cropland tends to have less carbon stored in both above- and below-ground biomass compared to natural ecosystems like forests and shrublands, although it can still store some carbon in the soil, which depends on agricultural practices.

The analysis of this study showed that forestland had the highest carbon stock of 258.94 t/ha, followed by shrubland of 169.21 t/ha, and cropland had the lowest carbon stock at 41.2 t/ha. In general, forests found in the Upper Awash River Basin have the highest total carbon stock, primarily due to their significant above-ground biomass, whereas croplands have the lowest total carbon stock, with all carbon stored in the soil. Shrublands have a lower total carbon stock compared to forests, but still contribute significantly to carbon storage.

Table 8. Carbon stock in different pools

LULC Class	AGC (t/ha)	BGC (t/ha)	SOC (t/ha)	Total Carbon (t/ha)
Forest	125.21	25.025	108.70	**258.94**
Shrubland	53.056	10.611	105.541	**169.21**
Wetland	0	0	76.444	**76.44**
Cropland	0	0	41.12	**41.12**

Figure 11 below shows the spatial distribution of carbon pools (t/p) in three different carbon storage categories across a specific geographic area. These categories are AGC, BGC, & SOC. The top left map represents carbon stored in the above pool, where green areas indicate high carbon storage, and most of the area shaded with pink indicates low carbon storage ($\leq$ 2.11). The top-right map represents carbon accumulated in roots & in the underground, whereas the bottom map represents the sum of carbon accumulated in the soil. Similar to AGC, the dominant colour is pink (low carbon level $\leq$ 0.451), and some green patches indicate areas with higher below-ground carbon.

The study showed that forests store the majority of their carbon in the above-ground biomass (trees), but they still have a significant amount of carbon stored in the soil. In the forest, 48.35% and 41.98% of the entire carbon stock was stored in aboveground biomass and soil, respectively, and the remaining 9.67% of carbon was kept in a belowground carbon pool, while 62.37% of the carbon was stored in the shrubland soil, 31.4% of the total carbon in shrublands is kept in above-ground biomass (mainly shrubs and small plants), and 6.3% is kept below ground in root systems. Shrublands have a smaller proportion of AGB compared to forests, but a larger share of carbon is kept in the soil, compared to forests, highlighting the importance of soil in these ecosystems for long-term carbon sequestration (Figure 11).

Wetlands act almost entirely as carbon sinks through soil storage, making them highly efficient at sequestering carbon. The results showed that 100% of the carbon in wetlands is kept in the soil as organic carbon, with no AGB or BGB contributing significantly. Hundred percent of the carbon in croplands is also stored in the soil. While croplands store carbon exclusively in the soil, their overall capacity to store carbon per hectare is much lower than in natural ecosystems like forests or wetlands. The total carbon stock in the basin was greater in the soil carbon pool, followed by the aboveground carbon pool (Figure 11). In the soil organic carbon map more variation in carbon levels, with yellow, green, and dark green areas showing moderate to high carbon storage, in which forest and shrubland regions have higher soil organic carbon than the rest of the LULC in the study area.

The AGC and BGC maps of the area have low values above and below carbon, indicating sparse vegetation or limited vegetation cover in the basin. The occurrence of green colour patches in both AGC and BGC maps showed vegetation land (forest and shrubland) that is important for carbon sequestration and storage. The difference in SOC distribution might be due to soil properties, land management, and vegetation cover that influence carbon storage.

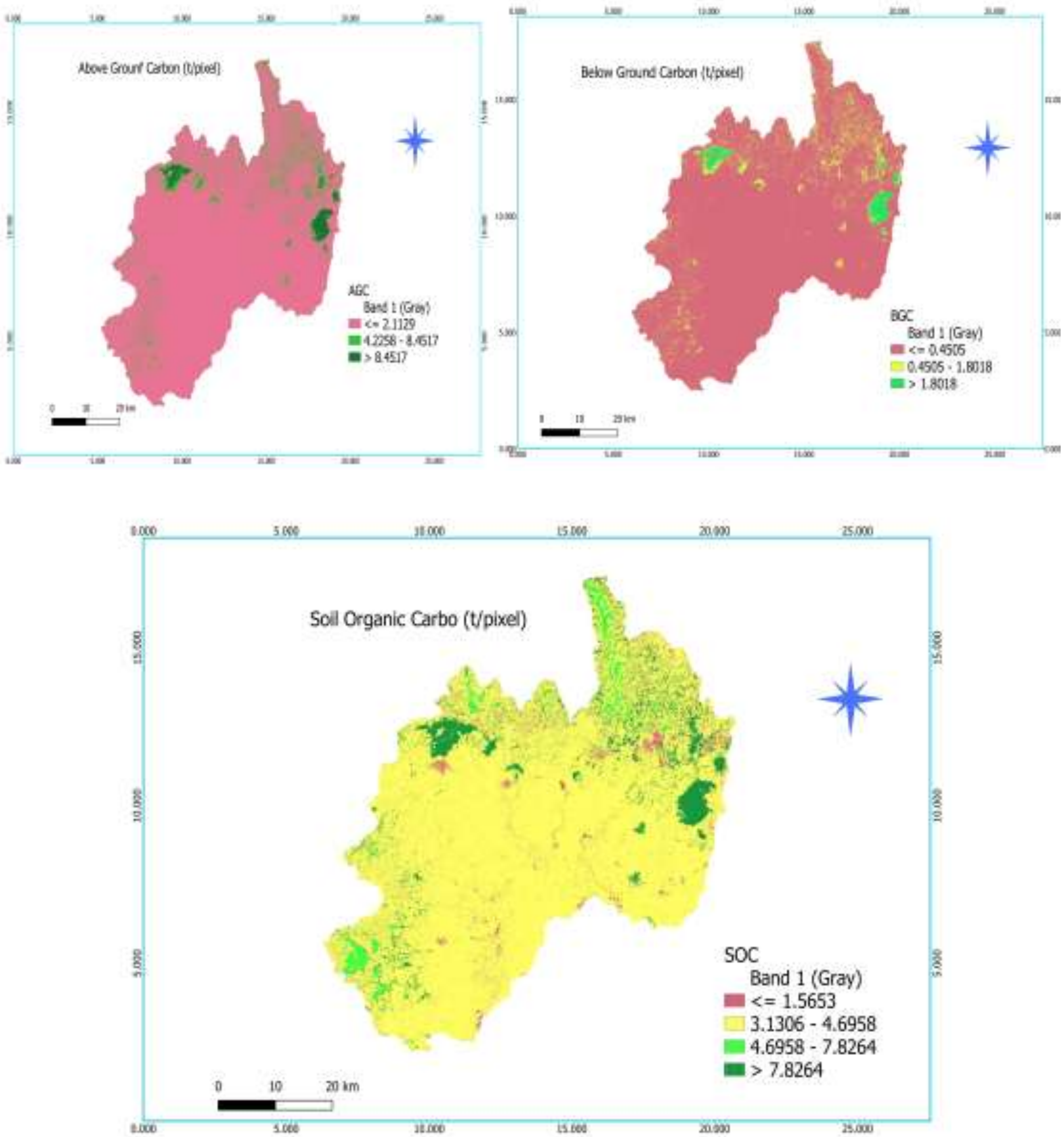


Figure 11. Spatial distribution of carbon pools (t/pixel)

4.2.2. Landscape carbon storage dynamics (1993–2023)

Table 9 presents carbon storage in tons of carbon (tC) for four land types: Forest, Shrubland, Wetland, and Cropland, across four different years (1993, 2003, 2013, and 2023). The results of the carbon stocks for each LULC class in the basin, estimated using the InVEST model, are presented in Table 9. The observed trends indicate significant carbon storage changes due to land use shifts. Carbon stocks, estimated from the InVEST model, showed values ranging from 41.12 to 258.94 t/ha, depending on the types of LULC and carbon pools in the study area.

The distribution pattern of carbon storage in the basin changed significantly (Figure 12). There's a noticeable decrease in forest carbon from 1,890,262 tC in 1993 to 1,372,382 tC in 2023, a drop of about 27%. This decrease could be due to deforestation, forest degradation, or changes in forest management practices over time. Shrublands show a decrease in carbon storage from 4,720,959 tC in 1993 to 2,758,123 tC in 2023, a drop of about 42%. This is a significant reduction in the carbon stored in shrublands, which could be linked to LULC changes such as agriculture expansion & urbanization. Shrubland showed the biggest loss between 2003-2013 but was stable from 2013-2023.

Wetlands experienced a sharp decline in carbon storage from 1,475,292 tC in 1993 to 580,944 tC in 2023, which is a dramatic decrease of about 61%. Wetlands are carbon-rich ecosystems, and this substantial drop may be attributed to the draining of wetlands for agricultural or urban development, and the degradation of wetland ecosystems over time. Wetlands experienced the steepest drop from 2013 to 2023, possibly due to agricultural expansion and urbanization. Cropland shows a steady increase in carbon storage from 9,256,112 tC in 1993 to 10,099,070 tC in 2023, an increase of about 9%. This increase could be the expansion of the cropland.

The entire carbon storage of the Upper Awash River Basin in 1993, 2003, 2013, and 2023 was 17,342,625, 16,505,173, 15,213,536, and 14,810,521, respectively (Table 9). The area's carbon storage has decreased over the past 30 years, with a cumulative loss of 2,532,113 tons. The total carbon stock has decreased from 17.34 million tC in 1993 to 14.81 million tC in 2023, a decline of approximately 15% over the three decades, while that in 85% of the areas remained unchanged. This reflects broader trends in land use changes where urbanization and agricultural expansion have led to reductions in natural carbon sinks like forests and wetlands while increasing carbon storage in cropland. Because of LULC change, the basin has experienced a significant loss of carbon stored capacity over the historical three decades (8.96 tons per hectare). (Table 9).

Table 9. Changes in carbon storage (1993-2023)

Year	Total Carbon (tC)				
	Forest	Shrubland	Wetland	Cropland	Total
1993	1,890,262	4,720,959	1,475,292	9,256,112	**17,342,625**
2003	1,657,216	4,077,961	1,291,836	9,478,160	**16,505,173**
2013	1,501,852	2,775,044	1,100,736	9,835,904	**15,213,536**
2023	1,372,382	2,758,123	580,944	10,099,070	**14,810,521**

Figure 12 below shows a set of four spatial distribution maps representing carbon stock changes over time from 1993 to 2023. The maps illustrate the variations in carbon storage across the basin, in which green areas indicate higher carbon stock due to dense vegetation or forest cover, while brown or yellow areas represent lower carbon stock, which could indicate deforested land, wetland, cropland, and built-up area.

The total carbon stocks lost between 1993 and 2023 were 517,880 tC, 1,962,836 tC, and 894,348 tC in forests, shrublands, and wetlands, respectively, with annual carbon losses of 17,262.67, 65,427.87, and 29,811 tons of carbon, while those in croplands increased by 842,960 tons of carbon in the last three decades (Figure 12). The estimated total carbon in the Upper Awash Basin for 1993 was 17,342,625 tons of carbon (61.35 tons/ha), while the estimated total carbon stock for 2023 was 14,810,521 tons (52.39 tons/ha) (Figure 12). Changes in carbon storage from 2003 to 2013 were the most obvious during the entire study period. The total carbon storage has decreased by about 2.5 million tons of carbon, suggesting that carbon-sequestering ecosystems like forests, shrublands, and wetlands are storing less carbon over time. With an average annual loss of 84,403.47 tons of carbon in the Upper Awash River Basin, the entire carbon stock has declined. This decline may be caused by land-use changes and environmental degradation.

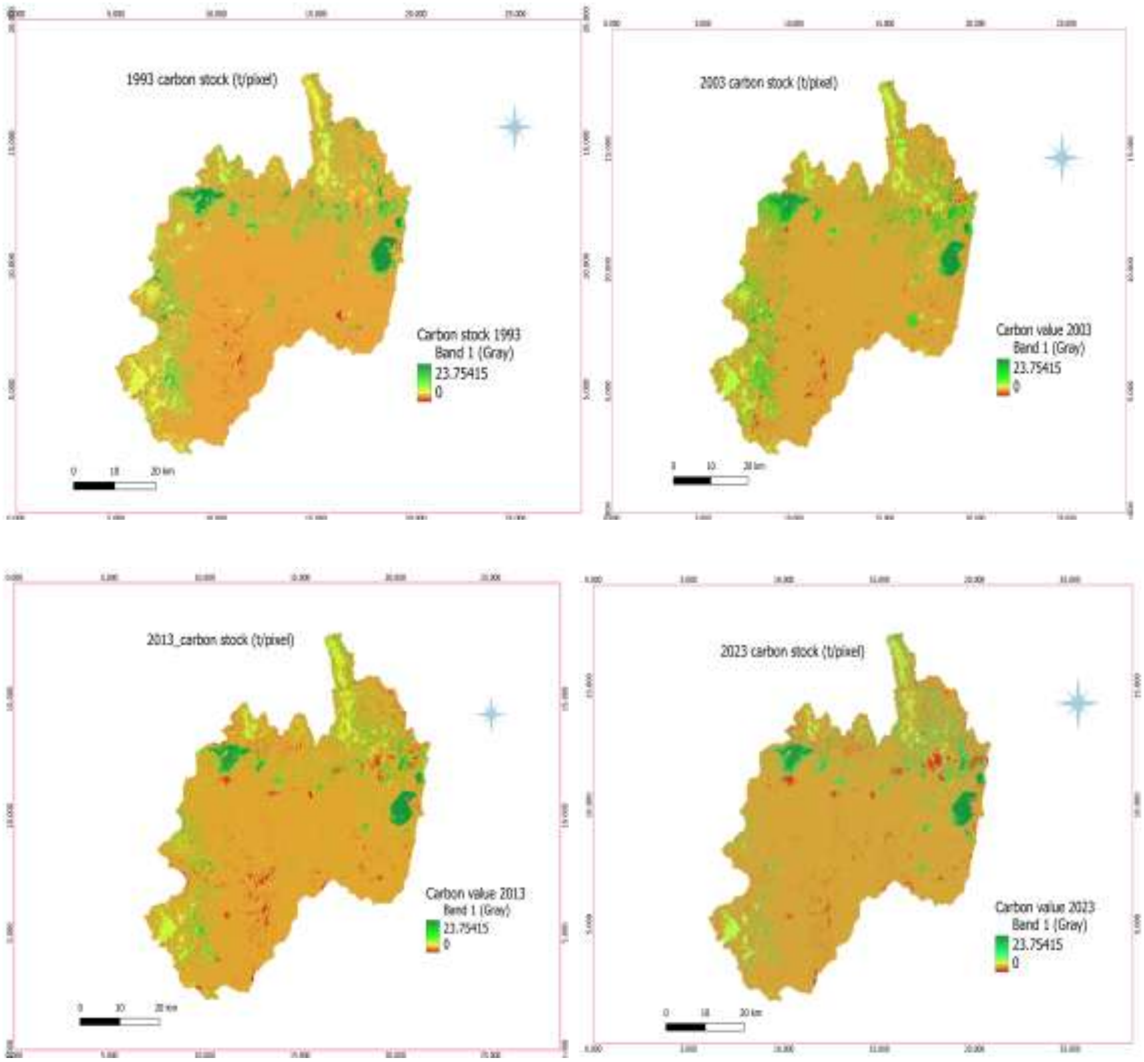


Figure 12. Spatial distribution of carbon stocks (1993-2023)

4.3. EFFECTS OF LULC CHANGES ON THE ENTIRE ECOSYSTEM'S SERVICES AND FUNCTIONS VALUES

4.3.1. Values of ecosystem services

Depending on the values given to each biome and land use dynamics, each LULC had a different ecosystem service value. The analysis of ESV across various LULC classes indicates significant trends and shifts over the last three decades, particularly from 1993 to 2023. In 1993, 2003, 2013, and 2023, the total ESVs were US$1959.06, 1913.52, 1867.1, and 1731.53 million, respectively, with a notable decline of US$227.54 million (Table 10). The result shows a significant shift in the relative contributions of land use types, with cropland and built-up areas increasingly dominating the ecosystem service value.

Cropland's ESV increased from US$ 1,253.36 million (63.98%) in 1993 to US$ 1,367.50 million (78.98%) in 2023 reflecting both cropland expansion & the intensification of agricultural production, whereas wetlands, shrublands, and forestlands experienced a decrease in their respective contributions to the entire values of ecosystem services (Table 10). Cropland has the largest share of the total ESV, and its value has steadily increased over the years. This is likely due to intensified agricultural practices, which may increase the economic value derived from agricultural production. However, this increased value comes at the cost of other LULC types (wetlands & forests) that have been converted to cropland. The result also shows the ESV for built-up areas has been steadily increasing over time, both in absolute terms and as a percentage of the total ESV, indicating that the ecosystem services built-up provide may become more significant, but they might also replace other land types that provide higher-value services (such as wetlands or forests).

The result shows that the contribution of forest ESV has declined both in total value and as a percentage of the overall ecosystem service value from $39.28 million (2.01%) to $28.52 million (1.65%) in overall ESV. This indicates a loss of forested land or a decrease in the environmental services provided by existing forests. The value of shrublands has seen a slight decline from $150.13 million in 1993 to $87.71 million in 2023. Wetlands, in particular, have seen a sharp drop from US$ 495.64 million in 1993 to US$ 195.18 million in 2023, indicating severe loss or degradation. This indicates the wetlands have been heavily impacted by human activities.

The total ESV has shown a decline from US$ 1,959.06 million in 1993 to US$ 1,731.53 million in 2023, marking an overall decrease of approximately 11.6%. This decline reflects the cumulative loss of ecosystem services provided by forests, wetlands, and shrublands, which have been replaced by cropland and built-up areas. The reduction in wetlands (which provide flood control, water purification, and carbon sequestration) and forests (which help mitigate climate change and preserve biodiversity) is particularly alarming. The result highlights a significant shift toward land use types (cropland and built-up areas) that provide short-term economic benefits but reduce the overall ecosystem service value. This trend suggests that ecosystem degradation is accelerating, which could have important implications for environmental health and human well-being in the long run.

Table 10. Total values of ecosystem services for every category of LULC (2007 US$ million ha^{-1} yr^{-1})

LULC class	Total ESV (2007 $ in Million Year−1)							
	1993		2003		2013		2023	
	Value	%	Value	%	Value	%	Value	%
Built-up	20.65	1.05	31.97	1.67	45.96	2.46	52.62	3.04
Forest	39.28	2.01	34.44	1.80	31.21	1.67	28.52	1.65
Shrubland	150.13	7.66	129.68	6.78	88.25	4.73	87.71	5.07
Wetland	495.64	25.30	434.01	22.68	369.81	19.81	195.18	11.27
Cropland	1,253.36	63.98	1,283.42	67.07	1,331.87	71.33	1,367.50	78.98
Sum	1,959.06		1,913.52		1,867.1		1,731.53	

4.3.2. Value estimated for ecosystem service functions

The 16 individual ecosystem functions of the basin were estimated for 1993, 2003, 2013, and 2023 using the methods of Costanza et al., (2014) (Table 11). Provision services (the production of food, the supply of water, raw materials, & genetic resources) saw steady increases in value over the years, with the total increasing from $993.54 million in 1993 to $1030.79 million in 2023. Provisioning services accounted for the largest portion of the overall services across the basin, followed by regulation, support, and cultural services. The average contributions were 50.7%, 52.4%, 54.5%, and 59.5% for provision services and 7.3% for cultural services across the four study periods.

Food production showed consistent growth, rising from $541.80 million in 1993 to $579.52 million in 2023. This could be attributed to increased agricultural productivity and more technologies or extension in food production. Food production and genetic resources were the two most significant contributors to the total service value, accounting for 55.4% and 28.5%, respectively. Water supply remained relatively stable, with only slight fluctuations (from $98.87 million in 1993 to $101.92 million in 2023), and raw materials experienced a slight decline over the years, from $62.65 million in 1993 to $ 59.70 million in 2023. This may reflect shifts in resource extraction methods, recycling efforts, or a move towards more sustainable alternatives.

Climate regulation, water regulation, and waste treatment were the three major contributors to the total regulation service value, accounting for 31.3%, 15.5%, and 26.7%, respectively (Table 11). Regulating services (such as water regulation, waste treatment, climate regulation, etc.) decreased overall from $609.74 million in 1993 to $415.16 million in 2023, a decrease of roughly 32%. The value of water regulation has sharply decreased, from $108.53 million in 1993 to $42.90 million in 2023. This decline could be a result of increasing pressure on water ecosystems, over-extraction of freshwater resources, and the degradation of wetlands or other natural systems that regulate water cycles. Waste treatment services and climate regulation declined from $151.78 million and $176.69 million in 1993 to $123.01 million and 155.95 million in 2023, respectively, possibly due to deforestation, land degradation, and the growing emissions from human activity. The result in Table 10 indicates that ecosystems are less able to regulate gases due to environmental degradation and the increasing complexity of anthropogenic activities in the basin. For instance, the value here decreased slightly from $0.42 million in 1993 to $0.26 million in 2023.

Supporting services encompass nutrient cycling, pollination, soil formation, and habitat. The nutrient cycle decreased from $33.16 million in 1993 to $13.08 million in 2023 due to LULC changes, deforestation, & intensive practices of agriculture. The value of pollination services has remained relatively stable, hovering around $6 million over the years, with a slight uptick in 2023 ($6.05 million). Soil formation services have seen modest growth from $120.24 million in 1993 to $130.96 million in 2023. The slight increase in soil formation indicates that natural processes like weathering, deposition, and organic matter decay continue to function, though this might also be due to efforts in soil conservation practices. However, the value still pales in comparison to provisioning and regulating services. Habitat services have sharply decreased from $48.75 million in 1993 to $19.50 million in 2023. This indicates a loss of biodiversity and habitats due to habitat destruction (such as deforestation and urbanization).

Cultural services provide non-material benefits like recreation, aesthetic values, and spiritual enrichment. Cultural services significantly declined, from $38.51 million in 1993 to $15.18 million in 2023, possibly due to urbanization, loss of traditional knowledge, or the degradation of natural landscapes that hold cultural value however, the value of recreation services slightly declined from \$109.44 million in 1993 to \$101.02 million in 2023.

The results in Table 11 clearly show that while provisioning services like food production and water supply have generally increased, regulating, supporting, and cultural services have declined significantly over the past three decades. This indicates that ecosystems are under increasing strain and their ability to regulate and support life on Earth is diminishing. The decline in regulation services, namely, the regulation of climate and water, reflects the growing environmental challenges that the basin faces, while the loss of supporting services like habitat provision and nutrient cycling highlights the ongoing loss of biodiversity and ecosystem integrity.

Table 11. The annual estimated value of each ecosystem service function (ESVf in million US\$ year^{-1})

Ecosystem Service Functions	Ecosystem Functions' Estimated Value (US\$ in millions)				Total
	1993	**2003**	**2013**	**2023**	**Total**
Provisioning Services					
Food production	541.80	551.93	568.94	579.52	2242.19
Water supply	98.87	99.92	102.15	101.92	402.86
Raw materials	62.65	62.15	62.01	59.70	246.51
Genetic resources	290.22	288.43	284.57	289.65	1152.87
Total	**993.54**	**1002.43**	**1017.67**	**1030.79**	**4,044.43**
Regulating services					
Water regulation	108.53	95.06	81.01	42.90	327.5
Waste treatment	151.78	146.12	141.04	123.01	561.95
Erosion control	86.26	79.00	70.62	53.37	289.25
Climate regulation	176.69	169.67	156.96	155.95	659.27
Biological control	26.11	23.96	21.79	15.55	87.41
Gas regulation	0.42	0.37	0.27	0.26	1.32
Disturbance regulation	59.95	52.48	44.46	24.12	181.01
Total	**609.74**	**566.66**	**516.15**	**415.16**	**2107.71**
Supporting Services					
Nutrient cycling	33.16	29.04	24.73	13.08	100.01

Pollination	6.01	5.99	5.93	6.05	23.98
Soil formation	120.24	123.05	127.57	130.96	501.82
Habitat/refuge	48.75	42.68	36.22	19.50	147.15
Total	**208.16**	**200.76**	**194.45**	**169.59**	**772.96**
Cultural services					
Recreation	109.44	110.26	110.31	101.02	431.03
Cultural	38.51	33.73	28.73	15.18	116.15
Total	**147.95**	**143.99**	**139.04**	**116.2**	**547.18**
Grand-total	**1959.06**	**1913.52**	**1867.10**	**1731.53**	**7472.28**

4.3.3. LULC changes' effects on ecosystem services and functions

Table 11 outlines the changes in ESV in millions of US dollars from 1993 to 2023 across various LULC classes. Tables 11 and 12 also show the LULC Changes' effects on environmental services and functions. The entire change in ESV across the basin was US$ 227.54 million, reflecting a 13.14% loss in ecosystem services across all land classes, and with the greatest decline recorded from 2013 to 2023 (Table 12 and Figure 13). Wetlands, forests, and shrubs had negative ESV values over all periods, whereas built-up areas and crops had positive values.

The ESV for built-up areas increased by $11.32 million, a significant growth of 54.84% from 1993 to 2003, and the increase slowed slightly, growing by $13.99 million or 43.75% from 2003-2013. Also, from 2013 to 2023, the increase continued but at a much slower rate, with $6.66 million and 14.49%. Overall, built-up areas experienced a total increase of $31.97 million or a 154.84% growth in ESV from 1993 to 2023. The rise in ESV from built-up areas indicates the expansion of urban environments, forests, shrublands, cropland, and wetlands. Although the growth slows in the later years, there’s still substantial growth overall, suggesting a steady increase in urban infrastructure and human-centric land use.

Shrublands have experienced significant degradation or loss, with the largest decrease occurring between 2003 and 2013, with a $41.43 million drop, or -31.90%. Between 1993 and 2003, shrublands saw a $20.45 million decrease, or -13.62% in ESV. The sharp decline in the earlier years shows a substantial loss of ecosystem services from these areas, possibly land conversion for agriculture or urban development.

The forest class has experienced a decline in ESV, with a total decrease of 27.40% over the same period (1993-2023), reflecting ongoing deforestation and land conversion pressures. Forests saw a decrease in ESV by $4.84 million (12.33%) and $3.23 million (9.38%) between 1993 and 2003 and 2003 and 2013, respectively. This loss is a cause for concern, as forests provide critical services like carbon sequestration, water filtration, and habitat for biodiversity. The results also showed a dramatic reduction in the overall ESV of shrubland by $62.42 million (41.58%) between 1993 and 2023. The decline of shrubland became more severe, with a $41.43 million drop (31.90%) between 2003 and 2013. This could indicate land conversion for agriculture or urban development. Wetlands experienced the most drastic and continuous decline in ESV, especially from 2013 to 2023 often linked to urban development and agricultural expansion. Wetlands have suffered the most severe decline, with a staggering total decrease of 60.62%.

The increase in ESV for croplands is likely due to the intensification of agricultural activities or the shifts of natural landscape to more productive cropland. A more substantial increase occurred between 2003 and 2013 by 3.77% ($48.44 million). Over the entire period, croplands saw a total increase of $114.14 million (9.11%). Though cropland shows positive growth in ESV, its relative contribution is much smaller compared to the dramatic losses in other classes like wetlands and forests.

Table 12. ESV changes for every category of LULC (2007 US$ million ha^{-1} yr^{-1})

LULC class	Changes in ESV (2007 US$ in Millions)							
	1993-2003		**2003-2013**		**2013-2023**		**1993-2023**	
	Value	%	Value	%	Value	%	Value	%
Built-up area	11.32	54.84	13.99	43.75	6.66	14.49	31.97	154.84
Forest	-4.84	-12.33	-3.23	-9.38	-2.69	-8.62	-10.76	-27.40
Shrubland	-20.45	-13.62	-41.43	-31.9	-0.54	-0.61	-62.42	-41.58
Wetland	-61.63	-2.44	-64.20	-14.8	-174.6	-47.2	-300.5	-60.62
Cropland	30.07	2.40	48.44	3.77	35.64	2.68	114.14	9.11
Total Change	-45.53	2.32	-46.43	2.49	-135.6	7.83	-227.5	13.14

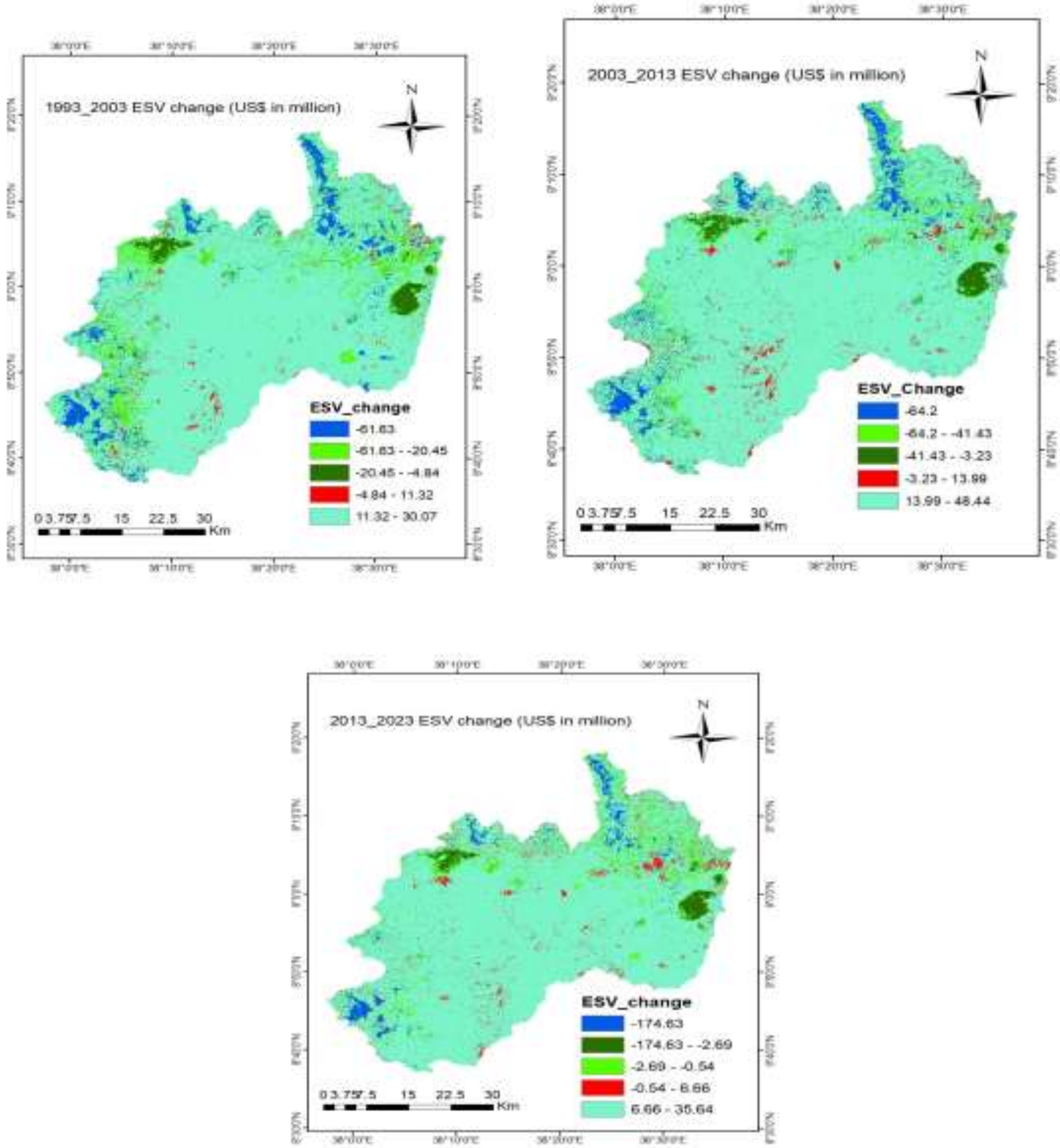


Figure 13. Changes in ecosystem service valuation (US$ in million)

Table 13 and Figure 14 present an overview of the changes in the ESV across four major ecosystem services (Provisioning, Regulating, Supporting, and Cultural) over three periods (1993-2003, 2003-2013, and 2013-2023). It also presents the shifts in the ecosystem function values from 1993 to 2023. Food production shows a steady increase over all periods, whereas water supply shows a small but steady increase followed by a decline Table 13. The value of food production has consistently increased, reflecting growing demand and improved agricultural practices, overall, a positive change of $37.72 million from 1993 to 2023. While water supply has generally increased over the first two periods, there has been a slight decline in the most recent decade. This could be due to increased pressure on freshwater resources or growing demand for water. Raw materials show a negative trend while genetic resources show a fluctuating but ultimately negative trend in the early periods and a positive trend in the most recent decade (2013-2023).

Regulating services show significant negative trends, particularly in water regulation and waste treatment, indicating deteriorating ecosystem health and increased pressure from human activities. Water regulation, waste treatment, and erosion control significantly declined by \$38.11, \$18.03, and \$17.25 million occurred respectively, between 2013 and 2023. The decline of climate regulation services may be linked to habitat loss and reduced carbon sequestration capacity of ecosystems due to land-use changes, which overall decreased by -\$20.74 million. While the first two periods show substantial losses in climate regulation services, the more recent decade shows a smaller decline (Table 13). Biological control and other regulatory services (e.g., gas regulation and disturbance regulation) also show declines, more or less showing a consistent negative trend over all periods.

Supporting services underpin other ecosystem functions, including nutrient cycling, soil formation, and habitat provision. Nutrient cycling and habitat provision show a negative trend in which a significant decline occurred between 2013 and 2023, whereas soil formation shows a positive trend. Although recreation services showed a small positive trend earlier, they have declined sharply (\$9.29 million) in the last decade (Table 13 and Figure 14). This may be due to urbanization, reduced access to natural areas, or environmental degradation that limits recreational opportunities. Cultural services show negative trends in all periods.

Table 13. Changes in the values of ecosystem function (US$ ESVf in million)

Ecosystem Service Functions	**Change in the value of ecosystem functions (US$ in millions)**			
	1993-2003	**2003-2013**	**2013-2023**	**1993-2023**
Provisioning-services				
Food-production	10.13	17.01	10.58	37.72
Water-supply	1.05	2.23	-0.23	3.05
Raw-materials	-0.5	-0.14	-2.31	-2.95
Genetic-resources	-1.79	-3.86	5.08	-0.57
Regulating-services				
Water-regulation	-13.47	-14.05	-38.11	-65.63
Waste-treatment	-5.66	-5.08	-18.03	-28.77
Erosion-control	-7.26	-8.38	-17.25	-32.89
Climate-regulation	-7.02	-12.71	-1.01	-20.74
Biological-control	-2.15	-2.17	-6.24	-10.56
Gas-regulation	-0.05	-0.1	-0.01	-0.16
Disturbance regulation	-7.47	-8.02	-20.34	-35.83
Supporting-services				
Nutrient-cycling	-4.12	-4.31	-11.65	-20.08
Pollination	-0.02	-0.06	0.12	0.04
Soil formation	2.81	4.52	3.39	10.72
Habitat/refuge	-6.07	-6.46	-16.72	-29.25
Cultural-services				
Recreation	0.82	0.05	-9.29	-8.42
Cultural	-4.78	-5	-13.55	-23.33
Sum	-45.53	-46.53	-135.56	-227.54

Figure 14 shows the change in the four ecosystem services, including provision, regulation, support, and cultural services in terms of monetary value (US$ million). All maps indicate the area of decline (negative value in red/blue) and increase (positive values in green or purple), highlighting spatial variations in ecosystem service changes over the 30 years. The change in the provision service map shows a mostly green landscape (cropland), indicating a positive change with some exceptional areas, particularly in the north and southeast, exhibiting negative values, indicating a decline in provisioning services. The change in the regulation services map shows a significant decline in some areas due to wetlands, shrubland, and forest ecosystem degradation and urbanization. The green areas in supporting services indicate stable services ($11.36 million), but some areas (red and blue) show a decline, with a maximum decline of $48.77 million. In the cultural services map, the dominance of pink indicates a significant reduction in cultural ecosystem services, with losses reaching $49.18 million.

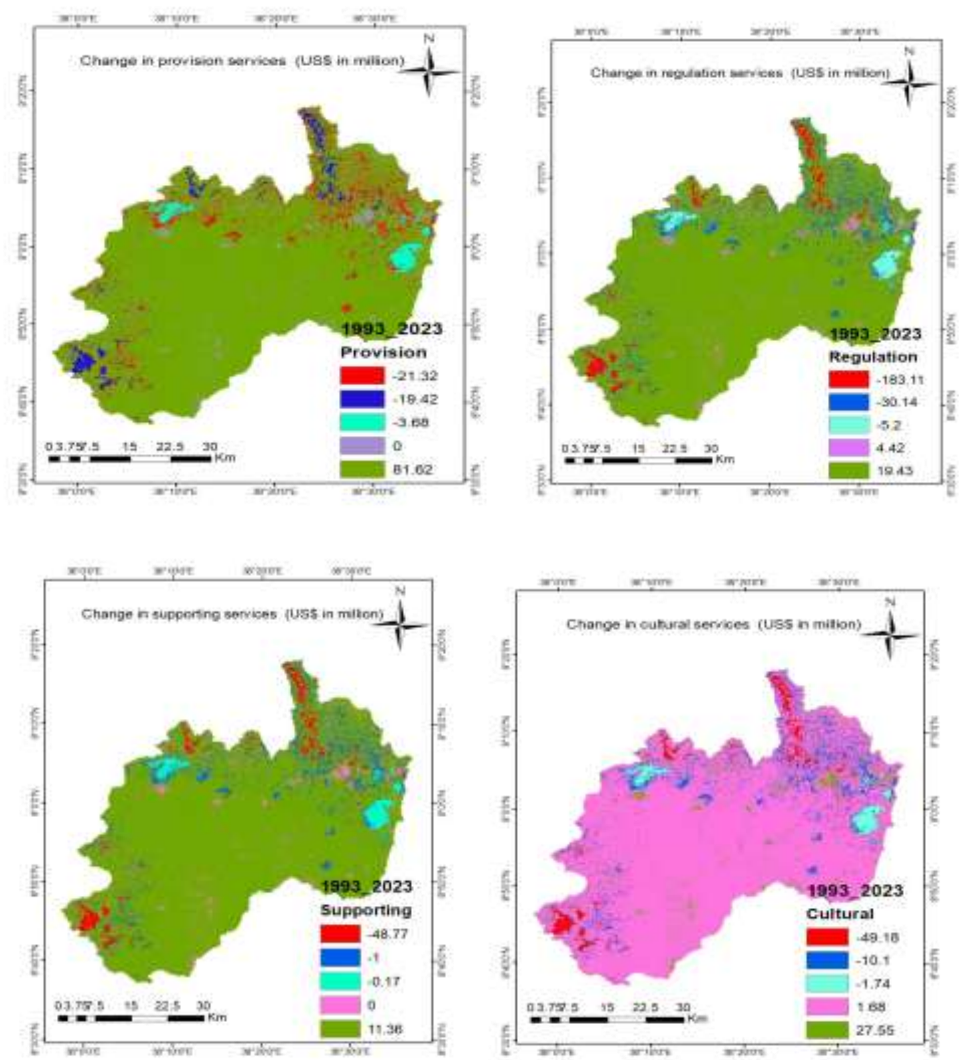


Figure 14. Changes in the values of ecosystem functions (US$ in million)

4.3.4. ESV sensitivity coefficient

Table 14 shows the Coefficient of Sensitivity (CS) for various LULC classes over four time periods: 1993, 2003, 2013, and 2023. The CS is often used to measure the degree of change or sensitivity of an ecosystem to a particular land-use class. Higher CS values generally indicate that the land-use class is more dynamic or more responsive to external factors, such as land-use change, policy shifts, or environmental stressors. However, the basin's sensitivity coefficient for all LULC categories was less than one, indicating that the value of environmental services was inelastic and that the methods used were reliable and robust (Table 14). Cropland had the highest sensitivity coefficient, ranging from 0.64 to 0.79, while forestland had the lowest (0.02) among all four periods. The CS for forested areas remains relatively stable at 0.02 across all years, indicating that they are relatively stable in terms of their interaction with other land use types. The consistency in CS could indicate that forest cover is less affected by the changes in the surrounding land use or environmental variables during this period. There is a gradual increase in the CS value for the built-up area over time, ranging from 0.01% to 0.03%. The CS for shrubland decreases over time from 0.08 in 1993 to 0.05 in 2023. The CS value for wetlands decreased significantly over the years. Wetlands show a marked decrease in CS over time, from 0.25 in 1993 to 0.11 in 2023, which might indicate a loss of wetland areas or a reduction in the ecological processes that make them sensitive to land use or environmental changes. Croplands contributed significantly to ecosystem services, followed by wetlands and shrublands (Table 14).

Table 14. Coefficients of sensitivity across LULC classes

LULC class	Coefficient Sensitivity (CS)			
	1993	**2003**	**2013**	**2023**
Built-up area	0.01	0.02	0.02	0.03
Forest	0.02	0.02	0.02	0.02
Shrubland	0.08	0.07	0.05	0.05
Wetland	0.25	0.23	0.20	0.11
Cropland	0.64	0.67	0.71	0.79

4.4. CARBON STOCK ESTIMATION USING VEGETATION INDICES

4.4.1. Remote sensing-based vegetation indices value

Several vegetation indices in the literature can be used to determine biomass and carbon stock. However, in this study, three types of vegetation indices were used to develop a proper correlation model for carbon estimation: NDVI, SAVI, and EVI. Figures 4 show NDVI, EVI, and SAVI maps generated using Landsat 8. The values in the three vegetation indices represent different levels of vegetation density, ranging from low (bare land or sparse vegetation) to high (dense vegetation). The index values varied across the basin, ranging from -0.1215889 to 0.7325657 (Figure 15). Higher NDVI values (green shades) are concentrated in the northern and some central areas of the basin, indicating healthier vegetation, while lower values (blue to red shades) dominate the southern parts (cropland and built-up dominant areas). The SAVI map closely follows the NDVI distribution but is adjusted for soil influence, making it more effective in distinguishing sparse vegetation in the basin. EVI provides clear differentiation of vegetation areas, with less soil and atmospheric noise compared to NDVI (Figure 15). The dense vegetation is prominent in the northern region, with decreasing density towards the south.

The values NDVI range from -0.12 to 0.48, where lower values indicate sparse vegetation. SAVI values range from 0.18 to 0.72, and EVI, which minimizes atmospheric and soil noise, ranges from 0.0 to 0.69, offering a clear distinction of vegetation density. The negative value of the vegetation indices indicates that the study area incorporates built-up & water bodies. The negative vegetation indices values are primarily associated with non-vegetated surfaces, including built-up areas, water bodies, snow, and bareland, reflecting the index's ability to differentiate between vegetated and non-vegetated areas.

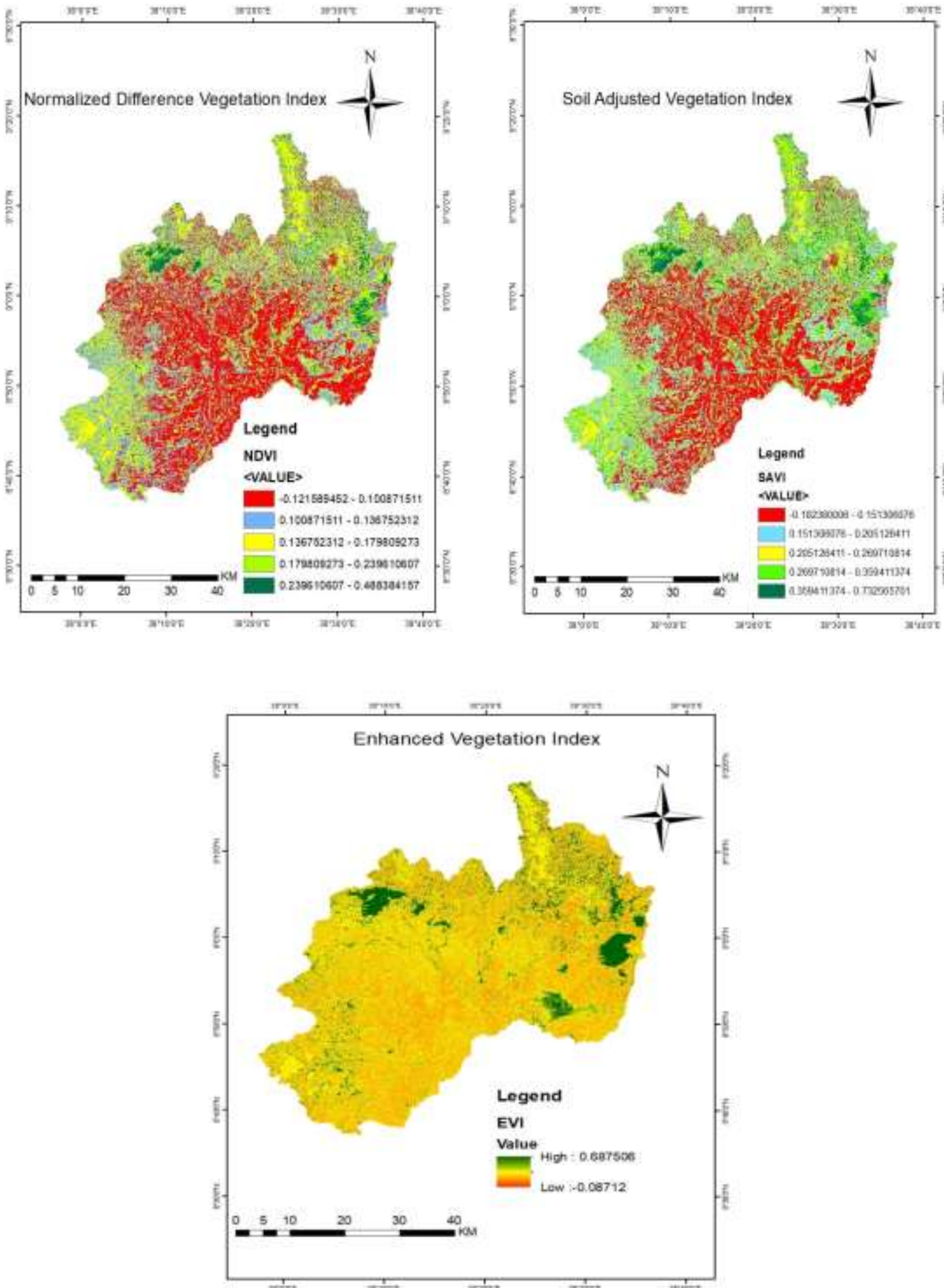


Figure 15. Spatial distribution of vegetation indices

4.4.2. Regression models between vegetation indices and field-level carbon stock

Figure 16 shows three scatter plots analyzing the relationship between vegetation indices (EVI, NDVI, and SAVI) and carbon stock (t/plot). The field-estimated carbon value ranges from 41.12 to 258.94 t/ha, with an average of 110 t/ha. The NDVI, SAVI, and EVI values range from -0.1215889 to 0.488384, -0.182380 to 0.7325657, and -0.08712 to 0.687506, respectively (Figures 15 & 16). The values pixel for to ever variable were extracted from ArcGIS, using field plot location (latitude, longitude) as a reference, and exported in CSV format. All computed information from the image and field plot is organized in one spreadsheet .csv format, and correlations were done in Excel to see which variable is more correlated with the field carbon stock. The scatter plots were drawn to show the relationship between carbon stock and the reflectance value of the derived indices. Regression analysis between vegetation indices (NDVI, SAVI, and EVI) and carbon value was performed using each value, represented by X (vegetation indices) and Y (carbon stock). The regression models use field-based carbon stock, NDVI, SAVI, and EVI values to develop equations. The derived equation was used to calculate the carbon stock of an area.

The regression analysis between NDVI, EVI, and SAVI values and carbon stock generated a model equation of $Y = 16.25x – 1.093$, $Y = 8.935x – 1.1254$, and $Y = 12.988x – 1.0895$ with coefficients of determination and correlation coefficient ($R^2 = 0.36$, $r = 0.60$), ($R^2 = 0.52$, $r = 0.72$) and ($R^2 = 0.36$, $r = 0.60$) respectively at p-value less than 0.05 (Table 15).

The equation for EVI, SAVI, and NDVI indicates that for every increase in respective indices (EVI< SAVI and NDVI), the carbon stock increases by approximately 8.94 t/plot, 12.99 t/plot and 16.25 t/plot respectively. EVI had the highest R^2 (0.52), making it the best predictor of carbon stock among the three indices. The R-value (0.717) for EVI indicates a strong positive relationship between EVI & carbon stock, whereas the R-value (0.61) for SAVI and NDVI indicates a moderate positive relationship among vegetation indices (EVI & NDVI) & carbon stock. The EVI model had a much lower standard error (0.130), indicating that the data points are very close to the regression line, indicating a better fit compared to the NDVI and SAVI models. As shown in Table 15 & Figure 16, for all three indices, the p-value is <0.001, indicating that the relationships between the independent variable and each of the indices (NDVI, SAVI, EVI) are statistically significant to develop a model.

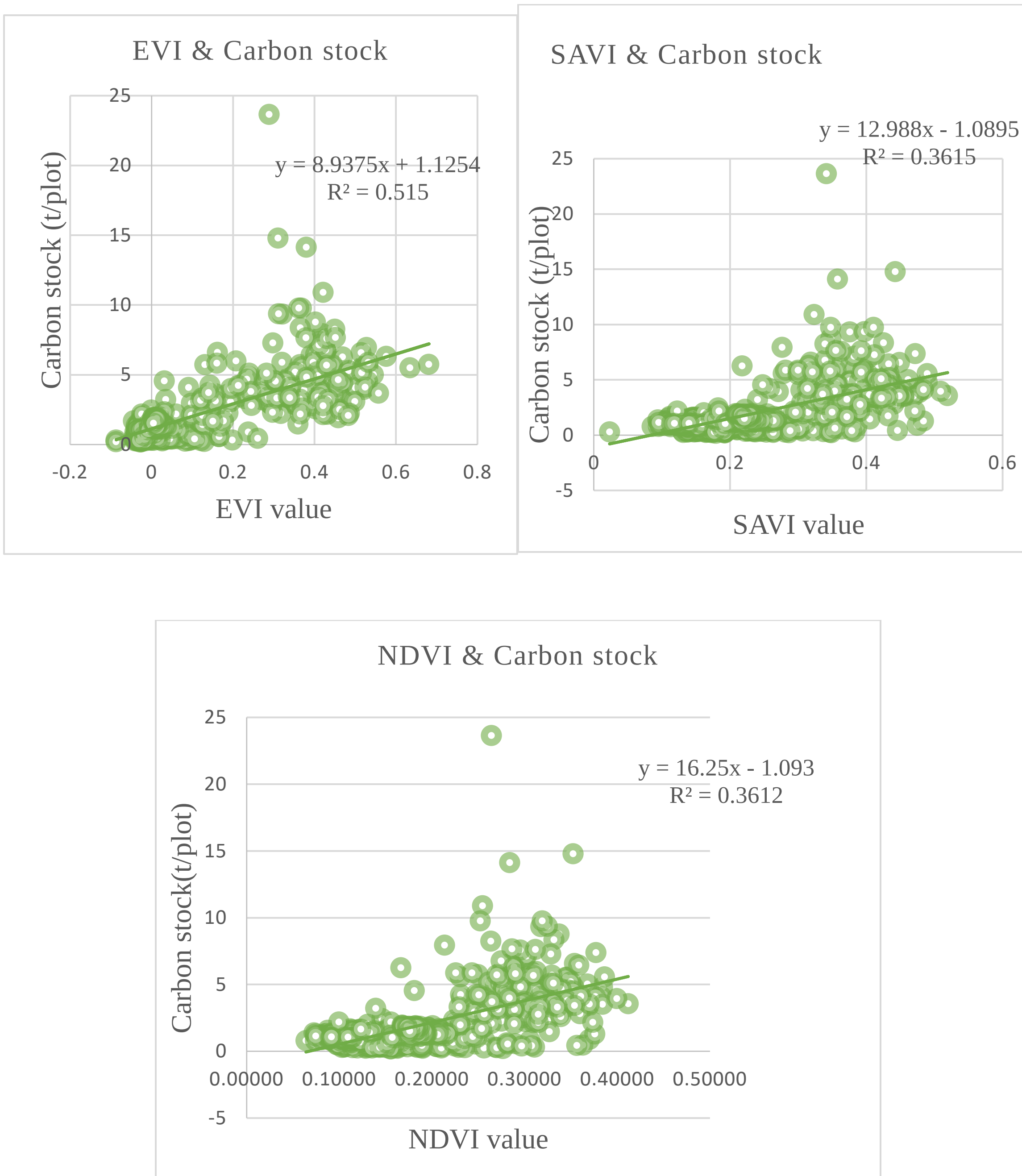


Figure 16. Linear correlation between vegetation indices and carbon stock

Table 15. Linear regression between observed carbon stock & vegetation indices

Indices	Linear regression model	Determination coefficient (R^2)	Correlation coefficient (R)	Std. Error	Sig
NDVI	Y = 16.25x – 1.093	0.3612	0.6	1.8631	<0.001
SAVI	Y = 12.988x – 1.0895	0.3615	0.6	1.8620	<0.001
EVI	Y = 8.935x – 1.1254	0.515	0.72	0.130	<0.001

4.4.3. Total carbon stock estimation based on vegetation indices and linear regression model

The entire carbon stock estimated in the basin using EVI was 15,904,158.24 tons, while the carbon stock values using NDVI and SAVI were 16,398,500.59 and 18,277,482.04 tons, respectively. The calculated carbon stocks in the study area using NDVI, SAVI, and EVI were 89.49, 94.93, and 111.96 tons per hectare, respectively (Tables 16, 17, & 18). While the first NDVI range covers the largest area, it contributes relatively less to the total carbon stock due to its low carbon stock per hectare (21.46 t/ha) (Table 16). Conversely, the maximum carbon stocks (196 t/ha) were found in smaller areas, highlighting the efficiency of carbon sequestration in well-vegetated zones. The fourth range (SAVI values between 0.35641 & 0.73257) has a relatively small area (12,926.7 ha), but its carbon stock per hectare is the highest, contributing 2,582,366.86 tons (Table 17). Although Range 4 (EVI values between 0.26971 & 0.35641) and Range 5 (EVI values between 0.27876 & 0.53211) have smaller areas, their carbon stock per hectare is significantly higher, particularly in Range 5 (236.49 tons/ha).

Table 16. Estimated carbon stock based on the NDVI linear regression model

No	NDVI Value	Area (ha)	Carbon stock (t/ha)	Total carbon stock (tons)
1	-0.12159 - 0.10087	93005.37	21.46	1,995,895.24
2	0.10087 - 0.13675	82646.64	44.38	3,667,857.88
3	0.13675 - 0.17981	62560.26	75.63	4,731,432.46
4	0.17981 - 0.23961	31541.76	110	3,469,593.60

5	0.23961 - 0.48838	12927.15	196	2,533,721.40
	Total	**282681.18**		**16,398,500.59**

Table 17. Estimated carbon stock based on the SAVI linear regression model

No	SAVI Value	Area (ha)	Carbon stock (t/ha)	Total carbon stock (tons)
1	-0.18238 - 0.15131	93008.52	24.57	2,285,219.34
2	0.15131 - 0.20513	82645.38	58.44	4,829,796.01
3	0.20513 - 0.26971	62559.27	81.52	5,099,831.69
4	0.26971 - 0.35641	31541.31	110.34	3,480,268.15
5	0.35641 - 0.73257	12926.7	199.77	2,582,366.86
	Total	**282681.18**		**18,277,482.04**

Table 18. Estimated carbon stock based on the EVI linear regression model

No	EVI Value	Area (ha)	Carbon stock (t/ha)	Total carbon stock (tons)
1	-0.02260 - 0.02627	121,916	38.72	4,720,587.52
2	0.026629 – 0.12345	86680	52.72	4,569,769.60
3	0.12345 – 0.17865	65964.08	79.9	5,270,529.99
4	0.17865 - 0.27876	6831	151.98	1,038,175.38
5	0.27876 - 0.53211	1290.1	236.49	305,095.75
	Total	**282,681.18**		**15,904,158.24**

CHAPTER FIVE

5. DISCUSSIONS

5.1. EVALUATING LAND USE LAND COVER CHANGE PATTERN

The study examines the effects of land use change (LULC) on ecosystem services and carbon stock dynamics in the Upper Awash Basin over the past 30 years (1993-2023). It uses satellite images, GIS techniques, and the InVEST model to analyze land cover changes and their impact on ecosystem services and carbon stock dynamics. The study also assesses the accuracy of remotely sensed LULC data using confusion matrices to improve reliability and applicability. The supervised LULC classifications for 1993, 2003, 2013, and 2023 showed high accuracy and Kappa values, enabling the detection of changing scenarios. According to Monserud (1990), Kappa values range from 0.70 to 0.85, showing excellent agreement between the classified images and ground truths. Also, another scholar indicates that a value of Kappa above 0.8 indicates substantial agreement, while the value of kappa between 0.6 and 0.8 suggests moderate agreement(Abbas Al-Aarajy et al., 2024). Thus, the results of the basin ensure that the derived classifications are reliable and can be utilized for scientific research, policy-making, and environmental monitoring.

The upper Awash Basin has experienced significant deforestation, forest degradation, and decreased shrubland and wetland areas due to built-up areas and cropland expansion. From 1993 to 2023, high forest areas decreased by 2,000 hectares, shrubland shrank by 11,600 hectares, and wetland areas dropped by 11,700 hectares. The growth in agricultural land is a key cause of LULC alteration, disrupting local hydrology and reducing water availability for ecosystems and human use. These findings are consistent with those of Giweta, (2018), Wassie, (2020), and Sisay, (2020), who found that Ethiopia has experienced significant forest degradation, deforestation, and a reduction in shrublands due to socioeconomic pressures and environmental factors. The upper Awash Basin's LULC changes over three time periods revealed a decline in wetlands, bushes, and woods and a rise in built-up regions and cropland. Forestlands experienced a significant decrease of 12.33%, 9.38%, and 8.62% in the first, second, and third periods, with the most significant decline linked to governmental changes and policy shifts (Amogne, 2014; Kindu et al., 2016).

Urbanization has contributed to the transformation of land cover in the upper Awash Basin, with built-up areas expanding as population centers grow. This urban spread frequently happens at the cost of forestland and wetlands, resulted to further ecological imbalance. Similar findings were reported in Ethiopia (Deribew, 2020; Enkossa et al., 2022), China, and India (Potapov et al., 2022; King et al., 2023), where urbanization and population pressure converted forests and shrublands to cropland and built-up areas.

Poor tenure systems and unclear land rights can contribute to unsustainable land use practices, while poverty may either exacerbate resource exploitation or limit the ability to adopt sustainable practices in the basin. These factors create a situation where land users, such as farmers and others, may not have secure ownership or long-term access to land. When land users lack secure ownership or long-term access, they often engage in unsustainable practices such as deforestation, overgrazing, and poor agricultural methods, which degrade the land and environment. For instance, insecure land tenure discourages long-term investments in land management, leading to practices like deforestation, overgrazing, and poor agricultural methods. These practices degrade the land and environment, as land users focus on short-term gains rather than long-term sustainability.

The percentage of the study area that was under cultivation increased from 79.63% in 1993 to 86.88% in 2023. This was mainly because of population growth, which caused an increase in demand for new cultivation land and settlements. For instance, according to a study by Genet (2020), Ethiopia's population growth has been closely related to significant LULC changes. The rapid increase in population has resulted in increased demand for cultivated land, grazing areas, settlement spaces, and resources such as fuel wood. The expansion of cultivated land into wetlands, forests, and shrublands has been a long-standing phenomenon in the central part of Ethiopia. In 1993, the total forest coverage was approximately 2.58% of the total study area, while in 2023, it decreased to 1.87%. This could be because of the deforestation activities that have been taking place to make space for agriculture. Sisay, (2020), also mentioned that agricultural expansion, resettlement programs, charcoal burning, and fuel cutting all contribute to deforestation in Ethiopia, resulting in a decrease in forest coverage. Following the fall of the socialist Derg in 1991, official control over forest resources was reduced, most of the forest and shrubland were deforested, and a few years later, new forest management legislation (1994 and 2007) allowed the local community to participate in forest management, especially in the Chilimo Forest Priority Area. However, in Ethiopia and specifically in the basin , deforestation continues due to a weak forest policy and poor implementation on the ground.

In the basin, all LULC variables, such as the spread of various agricultural activities, the production of fuelwood and charcoal, cutting trees for construction resources, settlements, and revenue growth, are associated with population increase and resettlement. This finding was consistent with that of Bahru et al. (2021) and Shumba (2001), who reported that the high demand for fuelwood, combined with population pressure, has resulted in overexploitation of these resources, contributing to deforestation, land degradation, and change in the climate. Getahun et al. (2017) similarly found that rapid population growth and associated resettlement efforts have boosted demand on natural resources, deforestation, and environmental degradation in certain parts of the country. Studies in Ethiopia and Asia have also revealed that population growth, urbanization, the expansion cropland, & deforestation are among the main drivers of LULC shifts (Garedew et al., 2009; Amsalu et al., 2007; Vadrevu et al., 2018; Geremew, 2013).

The results demonstrate the intricate relationship that exists between environmental preservation, the growth of economics, and human needs. The expansion of cropland and urban areas is driven by the basic human needs for food, shelter, and livelihood, which are fundamental rights that should be respected and protected. However, the overuse of natural resources and the destruction of the terrestrial environment in the process of meeting these needs raise important questions about the limits of human entitlement and the responsibilities towards the environment. The fact that poverty & tenure systems were defined as indirect drivers of LULC changes suggests that there are deeper structural and systemic issues at play, which require a more holistic and long-term approach to address. From a practical perspective, the goal should be to maximize the overall health and livelihood of current & future generations, which needs finding an acceptable compromise between immediate human requirements and conserving the environment for the long term. The high dependence on biomass energy in the Upper Awash Basin has put a significant stress on forest resources, leading to an unsustainable wood extraction practices. This situation is exacerbated by various socio-economic factors, including population density, poverty, and inadequate land tenure systems, which have contributed to the expansion of cropland into wetlands and the clearing of forests at alarming rates to meet rising food and energy demands. Infrastructure development, particularly road networks and urban settlements, plays a crucial role in LULC changes, further intensifying the degradation of forest ecosystems. Overgrazing by increasing livestock populations in forest areas has also led to forest degradation and negatively impacted regeneration. The same findings were previously published in China, indicating that population growth, infrastructure expansion, agricultural expansion, and government policies are major drivers of LULC change (Tan et al., 2024; Shang et al., 2023).

5.2. IMPACT OF LULC CHANGES ON CARBON STOCK DYNAMICS

The InVEST modeling tool was used to calculate carbon stocks in a study area, aiding in sustainable land management decisions. The model uses field sampling data to estimate carbon storage, reducing uncertainty and generating reliable results. The study considered three carbon pools, providing a comprehensive estimate of landscape carbon storage at the basin scale. High-quality, representative field measurements can significantly enhance the model's accuracy by providing reliable baseline data against which to compare model outputs (Li et al., 2022; Sun et al., 2022). Climatic influences significantly impact carbon stock estimates, requiring a comprehensive approach that considers local factors like topography, slope, and climate to accurately determine vegetation biomass and soil carbon sequestration rates. These factors can influence both the distribution of carbon stocks and their changes over time, necessitating localized assessments to enhance accuracy (Li et al., 2023). The InVEST model accurately estimates carbon stock by classifying different LULC types, enhancing reliability and minimizing uncertainty through efficient visualization of carbon storage data from field sampling.

The Upper Awash River Basin play significant role in carbon storage through its forests and shrubland, which are significant contributors to both aboveground and belowground biomass carbon stocks. The forests, especially the Chilimo and Menegasha Suba forests in this region, consist of diverse tree species that sequester carbon in their stem, twigs, & foliage. Additionally, the extensive root systems of these trees and other vegetation contribute to substantial carbon storage below the ground surface. Decomposed plant matter is the source of the soil's biological material, and the growth of bacteria raises the soil's carbon from organic matter stocks in the basin. The study suggests that conserving and improving soil organic carbon stocks can help sequester carbon, reduce GHG emissions, and promote sustainable land management.

Forest biomass stores more carbon per hectare than other LULC classes due to high biomass and organic matter decomposition in the forest. This process is fundamental to mitigating climate change, as forests can sequester significant quantities of carbon across their entire periods (Andl et al., 2006; Psistaki et al., 2024). Similarly, other findings indicated a greater carbon stock in forestland than in other LULC categories (Solomon et al., 2018; Rajput et al., 2017). Other scholarships found that forests, particularly the tropical Afromontane forests of Ethiopia, can sequester & accumulate more carbon within the tissues and soils than can other LULC types (Tadese et al., 2023; Nyirambangutse et al., 2017; Birungi et al., 2023).

The variation in carbon stocks between forests and shrublands might be due to variations stems quantity, population density, and diameter of the individual trees. This is in line with the results of Solomon et al. (2018), found that tree density and diameter have an effect on biomass carbon in northern Ethiopia. Gebeyehu et al. (2019) and Muluneh & Worku (2022) also highlight that changes in carbon stocks are caused by a variety of factors, including disturbance levels, environmental gradients, site characteristics, land use types, and interactions between biotic and abiotic factors within ecosystems. Solomon et al. (2017) and Solomon et al. (2018) stated that forestland have greater carbon stocks than shrublands due to their greater biomass density and tree cover.

Over the study period, changes in LULC have resulted in a significant loss of carbon storage in the basin, most of which has occurred in forest and shrubland areas. The results showed that the cropland in the study area expanded rapidly from approximately 225,100 ha in 1993 to 254,600 ha in 2023, while the overall percentages of forest, shrubland, and wetland decreased by 27.4%, 41.58%, and 60.62%, respectively. Most of the area lost from forests, wetlands, and shrubland was converted to cropland. This dramatic shift in LULC in the basin has led to carbon stocks in forestland decreasing from 1,890,262 tC to

1,372,382 tC over 30 years, with an average annual loss of 17,262.67 tC. Conversely, the carbon stock in cropland increased from 9,256,112 tC to 10,099,072 tC, with an average annual increase of 28,098 tC. Over the study years, the amount of carbon stored in the basin has significantly decreased (8.96 tons per hectare) due to LULC change. The change has occurred in forests, shrublands, and wetlands, while cultivated land shows an increased carbon stock. This is because the cultivated land area expanded to other land uses, and the land cover increased by 9% within the same period.

The LULC transformation was mainly from land with high carbon density to land with low carbon density, as shown in the transformation from forest, shrubland, and wetland to cropland. The results showed that there was a decrease in the total carbon stock of 15% from 1993–2023. The decrease can be attributed to the decrease in the total area of LULC classes with high carbon values, such as forest, shrubland, and wetland. This was also supported by the rapid urbanization in the area caused by deforestation and land cultivation in the upland region over the years. These findings are consistent with those of Toru & Kibret (2019) and Tadese et al. (2023), who reported that LULC with high carbon density, such as forest, shrubland, and wetland conversion, reduce carbon stocks, affecting vegetation and soil organic carbon. Among the land uses, forest was found in Chilimo, and Menegesha had the largest average estimated carbon stock per hectare. Additionally, this outcome is in line with the conclusions of Kassahun et al. (2015) and Toru & Kibret (2019), who reported that forests have a greater average estimated carbon stock per hectare than other land uses.

In general, the Upper Awash Basin in Ethiopia has experienced significant changes in soil organic matter due to land use transitions, particularly from forested areas to cultivated land. Research result in the study area indicates that soils from croplands exhibit lower organic matter values compared to those from forested regions. Changing land use from forest to cropland depletes nutrients and soil organic matter. Intensive cultivation in the Upper Awash Basin has a significant negative impact on soil carbon stocks. In line with these results, cropland that has undergone intensive cultivation or other anthropogenic soil disturbances has a lower carbon stock, and land uses that include woody perennials have a higher carbon stock than those that do not (Toru & Kibret, 2019). Soil cultivation reduces organic matter by facilitating the interaction of physical, biochemical, & organic soil processes that increase the decomposition rate of SOM (Solomon et al., 2000). Amanuel et al. (2018) and Sharma & Sharma, (2022) also found that frequent tillage practices severely deplete soil nutrients and organic matter when forestland is converted to agricultural use.

A basin is a vital region supporting agricultural activities and natural ecosystems. However, human activities, primarily driven by the growth of population & the development of economics, have led to changes in LULC that impact the climate system. Similarly, studies by Dessu et al. (2020), Wassie (2020), and Regasa et al. (2021) show that human activities, driven by population growth, resettlement programs, and poor governance, have led to notable LULC changes in Ethiopia, with adverse effects for the environment & local communities. The study also confirmed that the increasing demand for tree products such as wood for fuel, building materials, & charcoal for domestic use in and around the District towns found in the study area was one of the major causes of LULC change that resulted in the net loss of carbon stock in the basin. This result was aligned with the study by Gashaw et al. (2018) and Gashaw et al. (2014), which found that the main causes of LULC changes in the country were the growing need for agricultural land, wood for fuel & construction poles, population growth, and inadequate natural resource conservation policies.

Land use change in the basin has led to a decline in terrestrial carbon stocks, primarily due to the conversion and degradation of forests, shrubs, and wetlands. This change in LULC contributes to change in the climate by releasing or sequestering carbon. These effects were also confirmed by Solomon et al., (2018) & (Tadese et al., 2023), who found that land use & land cover changes, particularly areas of cropland and built-up expansion at the cost of forestland & other natural ecosystems. The carbon release from the LULC changes contributes to climate change, stressing the necessity of environmentally friendly land preservation methods to conserve and restore carbon sinks in the country. For instance, carbon stocks are frequently lost when natural vegetation is turned into farmland and built-up areas, especially in forests that store large amounts of carbon. Moisa et al. (2023) and Muluneh & Worku (2022) also confirmed these findings, stating that the alteration of natural ecosystems, particularly forests, to other LULC in Ethiopia has resulted in significant carbon stock losses due to carbon release from vegetation and soils. This has implications for the region's efforts to mitigate climate change. The expansion of agricultural activities, including the cultivation of annual crops and grazing, has resulted in the clearing of forests and the degradation of wetlands. This has not only led to the immediate release of carbon stored in vegetation but also reduced the possibility of a carbon sink in the future. Eshete et al. (2020) discovered that agricultural expansion, particularly through unsustainable practices and land use change, highly increases GHG emissions, causing changes in the climate by altering local microclimates and influencing temperature & rainfall patterns in the basin.

In the study area, land degradation resulting from improper practices of land management, like soil erosion & degradation, can also lead to carbon loss. When soils are eroded or degraded, the soil organic matter & its carbon content are reduced. This reduces the capacity of the land to sequester carbon and contributes to the release of carbon dioxide into the lower atmosphere. The key drivers of carbon storage loss are the expansion of cropland, the over-extraction of forests for fuel wood and charcoal, settlements, population growth, and urban expansion. Land-use changes from forests to croplands have a far more significant impact on carbon storage by releasing atmospheric CO_2. The main underlying processes associated with LULC change and carbon stock loss are population density and distribution, poverty, and a poor tenure system, which results in built-up and cropland expansion to wetlands, forests, and shrublands. The expansion of agricultural activities in the basin, driven by the growth of population & food demand, often leads to deforestation and LULC changes, contributing to carbon emissions & changes in the climate elements. A basin is home to ecosystems like forests and agricultural lands, which contribute to carbon sequestration. However, LULC and climate change have increased carbon emissions, necessitating an understanding of carbon stock dynamics for effective climate change mitigation plans.

5.3. IMPACTS OF LULC CHANGES ON THE ECOSYSTEM SERVICES

The assessment of ESVs in the basin from 1993 to 2023 reveals a notable decline, primarily driven by LULC changes. Over this period, the overall ESV decreased by 13.14%, primarily due to increased agricultural expansion, deforestation, and urbanization. The value of cropland ESV increased significantly, from US$ 1,253.36 million (63.98% of total ESV) in 1993 to US$ 1,367.50 million (78.98%) in 2023. This shift indicates a trend towards more intensive agricultural practices, reflecting a prioritization of food production over ecological balance. In contrast to cropland, wetlands, shrublands, and forestlands experienced a reduction in their contributions to the overall ESV. This decline underscores the biodiversity loss & ecosystem functionality due to changes in habitat and degradation. The same findings by Kindu et al. (2016), Gashaw et al. (2018), and Tolessa et al. (2018) reported losses in ESVs due to the shifts in LULC from one particular type of land use to another in various regions of Ethiopia. Another research in Dire and Legedadi watersheds indicates that between 1985 and 2022, natural vegetation and grasslands declined significantly while settlements and cultivated lands increased. This shift has led to a loss in ESVs from approximately $65.8 million to $11.9 million in certain watersheds (Admasu et al., 2023). The loss of ESV including carbon sink, soil fertility, and water purification, directly impacts local communities' livelihoods and overall environmental health.

Forestlands provide the provision, regulation, support, & cultural ecosystem services that are vital to human health and the health of the environment. It helps to slow down global warming by acting as a carbon sink. However, deforestation in the Upper Awash River Basin significantly affects ESVs through various mechanisms that disrupt ecological balance and diminish the benefits provided by natural systems. The removal of forest cover in the basin increases soil erosion rates, leading to the loss & degradation of soil. This degradation can reduce agricultural productivity and increase the expenses connected to soil restoration & management. Similarly, according to research by Daba & You, (2022), the conversion of forested areas into agricultural and urban spaces has further exacerbated the decline in ESVs, particularly affecting climate regulation and habitat services. Consequently, the ESVs associated with soil health and agricultural outputs decline. Also, deforestation in the area often reduces the availability of resources that local communities rely on for their well-being.

Changes in LULC significantly affect water ecosystem services in the Upper Awash River Basin, primarily through alterations in vegetation cover, hydrological dynamics, and water quality. The research in the basin indicated that a shift in vegetation cover reduces the ecosystem's ability to regulate water flows, leading to increased runoff & diminished groundwater revive capabilities (Besha et al., 2024; Hirpa et al., 2023). As a result, the availability of water for both human use and ecological functions diminishes, negatively impacting water supply services in the basin. Environmental services, for instance, improved water quality, recreation, climate mitigation, erosion, and biological control, are all negatively impacted by the decrease in ESVs. Muche et al., (2023) and Biedemariam et al., (2022) also highlighted the effects of human-induced changes in LULC on ecosystem degradation, biodiversity loss, and economic poverty in Ethiopia. Regulation, support, and cultural services showed a decreasing pattern while provisioning services showed an upward trend. Between the years 1993 and 2023, provisioning ecosystem services increased by US$ 37.25 million, whereas regulating ecosystem services decreased by US$ 194.58 million because of cropland expansion to forestlands, shrublands, and wetlands. Similar trends were observed in studies conducted in the Blue Nile Basin, Northern Ethiopia, and the Central Highlands (Berihun et al., 2021; Biratu et al., 2022; Solomon et al., 2019).

The expansion of croplands has significantly increased food production, but it has also led to a considerable decline in various ecosystem services such as wastewater treatment, erosion & biological control, regulation of water, gas, & climate. Over the past three decades, from 1993 to 2023, the conversion of land to cropland has resulted in a loss of ecosystem service values (ESVs) estimated at approximately US$ 227.54 million. This decline has resulted in the loss of forests, shrubs, and wetlands, which are crucial for maintaining ecosystem balance and services. Kindu et al. (2016) and Tolessa et al. (2018) reported similar results. Muche et al. (2023), Biedemariam et al. (2022), and Assefa et al. (2021) highlighted the decline in the extent of forest and ecosystem service values in the country. The estimated loss of millions reflects not only the economic value of these functions but also highlights the long-term sustainability challenges posed by current agricultural practices. The trade-offs between the increased production of food & declining environmental services emphasize the stipulation of sustainable land management practices. Policies that integrate agricultural productivity with environmental preservation are essential to mitigate the adverse effects of LULC changes on vital ecosystem functions & services.

The cumulative effects of reduced coverage of plants & hydrological dynamics diminish the ecosystem's ability to deliver essential services, namely, improved water quality, recreation opportunities, climate mitigation, erosion control, and biological regulation. As ESVs decline, clean water availability for domestic use & ecological functions decreases. In general, changes in LULC owing to the growth of agricultural land, urbanization, deforestation, poverty, and other factors affect ecosystem services. In the basin, the changes in LULC have led to a considerable loss of ESV, with the majority of the loss happening in areas of wetlands, forestland, and shrublands. Forestlands, shrublands, and wetlands are being replaced by croplands and built-up areas, which significantly impact ecosystem service values, for example, the regulation of water & climate, provision of food, biological and erosion control, and waste management. As a result, ecological services are deteriorating, threatening local communities' livelihoods. If current trends in LULC continue, cropland's ESV share could increase, with serious consequences for overall ecosystem services. Continued trends in LULC could increase cropland ESV, with serious consequences (Admasu et al., 2023). Shiferaw et al., (2023) stated that the importance of environmental services in forestland and grazing lands decreased, while that of agricultural land increased. Deforestation can accelerate local climate warming, affecting agricultural productivity and decreasing pollination, water regulation, biological control, nutrient cycling, and genetic resources (Admasu et al., 2023; Daba & You, 2022).

LULC changes can influence climate patterns such as temperature, precipitation, and carbon sequestration, which affect climate regulation services. Converting forestland, shrublands, and wetlands to agricultural land reduces carbon sequestration and increases soil erosion, highlighting the significance of assessing the effects of the changes on ESV (Feranec & Soukup, 2012). Thus, the findings underscore the importance of strategic planning that balances agricultural needs with ecological integrity, ensuring sustainable management of natural resources while enhancing ecosystem resilience against ongoing environmental changes. Implementing policies that support ecological restoration could yield significant long-term benefits for both biodiversity conservation and human well-being in the region.

5.4. CARBON STOCK ESTIMATION USING VEGETATION INDICES

Carbon stocks in the Upper Awash River Basin have been evaluated via a combination of ground truth data & satellite-based vegetation indices, specifically the NDVI, SAVI, and EVI. These indices leverage remote sensing data to correlate vegetation characteristics with carbon stock, enabling assessments across different LULC types. They provide valuable insights into vegetation health and distribution across different LULC types. Similar studies have been conducted on vegetation indices with data from Landsat 8 OLI, which gives a full thoughtful of the stress levels brought on by changes in LULC and urbanization, as well as the health and distribution of vegetation (Habib & Al-Ghamdi, 2021; Manandhar et al., 2009). Landsat 8 OLI features improved spectral bands compared to its predecessors, including two new bands specifically designed for cloud detection. This enhancement allows for more accurate vegetation assessments and the ability to distinguish between various land cover types more effectively (Chaves et al., 2020). In general, Landsat 8 OLI is a powerful tool for researchers and practitioners in the field of RS, particularly for vegetation indexing & environmental monitoring. It allows the ability to precisely evaluate and monitor vegetation health, biomass, and carbon stocks. Combining field data with satellite-based vegetation indices generate more precise and comprehensive information about carbon stock. Models were created to investigate the correlation between vegetation indices and field inventory-based carbon stocks. This model correlated NDVI, SAVI, and EVI values with field-based carbon stocks in 2023.

Based on the results of the regression study, parameter with high coefficients of determination and coefficients of value were chosen for carbon stock estimation. The linear correlation was high, indicating a strong relationship when estimating a region's carbon stock. In the Upper Awash Basin, EVI has a significantly stronger linear correlation with carbon stock than NDVI and SAVI. This means EVI is the most reliable vegetation index for estimating the carbon stock. This could be because EVI improves NDVI by accounting for atmospheric conditions and soil background, resulting in a more accurate representation of plant growth (Vidican et al., 2023). According to (Jiang et al., 2007; Matsushita et al., 2007), EVI is a more effective vegetation index than NDVI and SAVI because it detects small changes in biomass, reduces saturation, and improves soil correction.

The estimated carbon stock in the Upper Awash River Basin using EVI was 111.96 tons per hectare. The study indicates that forested areas within the Upper Awash River Basin exhibit significantly high values of vegetation indices, reflecting robust vegetation health. In contrast, built-up areas and croplands show lower values, suggesting reduced vegetation density and health in these regions. This pattern is consistent with findings from other studies that highlight the effectiveness of NDVI, SAVI, and EVI in differentiating between various land cover types based on their biomass and vegetation density (Shafique et al., 2021; Habib & Al-Ghamdi, 2021). The findings by Muhe (2019) in the Yayu forest land of Ethiopia showed that the carbon stock per hectare ranges from 150 to 250 tons per hectare; however, in degraded land, it dropped to 70.5 tons per hectare. Another study conducted in northwest Ethiopia revealed that the tons per hectare varied from 131 tons for plantation forests to 191 tons for natural forests (Kendie et al., 2021). The mean total organic carbon stock varied from 138.95 tons per hectare in the cropland to 496.26 tons per hectare in the natural forest in the Hades sub-watershed study conducted in eastern Ethiopia (Toru & Kibret, 2019). As per the guidelines set forth by the IPCC, the average carbon stock in forests is approximately 162 tons per hectare, of which about 72 tons are contributed by the soil (Pandey, 2012). However, the data on carbon stocks is still limited for most countries. The accuracy of the carbon stock estimates using NDVI, SAVI, and Several factors influence EVI, including the quality of the satellite data, the precision of the ground-based observations, the degree of connection between the vegetation indices and carbon stock, and the geographic resolution of the data (Malik et al., 2022; Marga, 2022).

Estimating carbon stock using vegetation indices is vital for climate change mitigation as it informs strategies for carbon sequestration and sustainable management of forest resources. All the indices show a strong positive correlation with carbon stock. The findings of the linear regression investigation showed that there is a positive & strong correlation between the amount of carbon stock estimated by ground inventory and the spectral vegetation indices (NDVI, EVI, and SAVI) of the study area. This correlation indicates that vegetation indices such as NDVI, EVI, and SAVI can be used to estimate carbon stock, and the relationship is adequate to provide accurate estimates. A similar study in the central part of Nepal has shown a strong positive correlation between vegetation indices derived from satellite imagery and field-measured carbon stocks (Marga, 2022). This indicates that efficient and economical assessment of carbon stocks over wide areas is made possible by remote sensing techniques that employ vegetation indices such as the NDVI and EVI (Shafique et al., 2021). Similar to these findings, vegetation indices are widely used in RS applications to estimate forest carbon stock & biomass because of their ability to capture vegetation spectral signatures and provide accurate estimates of carbon sink potential (Shafique et al., 2021; Malik et al., 2022). In comparing different vegetation indices for estimating carbon stock in the different areas, several studies highlight the effectiveness of NDVI, EVI, and SAVI. Each index has unique strengths and applications based on its sensitivity to vegetation characteristics and environmental conditions.

EVI is more sensitive to minor shifts in vegetation biomass and is less prone to saturation in dense vegetation areas, making it more effective at detecting changes in vegetation health and vigor (Vidican et al., 2023). EVI maintains sensitivity across a wider range of biomass levels, allowing for more accurate assessments in densely vegetated areas, whereas NDVI tends to produce similar values for both low and high vegetation densities, leading to inaccuracies in carbon stock estimation (Habib & Al-Ghamdi, 2021). Also, other studies confirm that EVI is designed to enhance the vegetation signal by minimizing atmospheric influences and soil background effects. It has been shown to perform better than NDVI in high biomass areas due to its reduced saturation effect (Marelign, 2022; Khan et al., 2020). Other studies showed that SAVI incorporates a soil adjustment factor, making it advantageous in areas with sparse vegetation where soil reflectance can skew results. This index is beneficial for estimating carbon stocks in semi-arid regions or areas where vegetation cover is sparse (Sousa Júnior et al., 2023). Assessing accurate information on carbon stocks from vegetation indices is essential in developing national greenhouse gas inventories and fulfilling reporting obligations under global accords (Khan et al., 2020). For instance, the REDD+ programs, which help to mitigate climate change through sustainable land management & forest conservation, can be implemented with the help of this information.

Carbon stock estimation is an important component in addressing change in climate change, influencing both policy and practical management strategies across various ecosystems. For instance, accurate carbon stock assessments support effective climate policies by providing essential data for decision-making. This includes identifying areas for conservation and potential carbon trading opportunities. The assessment of carbon stocks supports environmental sustainability and offers economic opportunities for rural development through carbon trading mechanisms. Understanding and managing carbon stocks can enhance forest conservation, promote sustainable land use practices, and contribute to global climate goals. Thus, by estimating carbon stocks, policymakers can develop strategies that mitigate carbon emissions through improved land management practices. This is vital for achieving targets set by international agreements such as the Paris Agreement.

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

This study evaluated the effects of LULC changes on ESV and carbon stock shifts of the basin from 1993 to 2023 using a comprehensive methodology that integrates remote sensing, ArcGIS, the InVEST model, and the regression model. The analysis revealed significant transformations in land cover, with noticeable declines in forestland, shrubland, and wetland areas, alongside expansions in cropland and built-up areas as it is compared to its original size of 30 years back. This transformation was primarily driven by agricultural expansion, wood extraction, and urbanization. These direct drivers have been exacerbated by indirect factors like population growth, poverty, and the land tenure system, which further intensify pressure on the environment.

The decline in forested areas has led to a significant reduction in carbon stocks, with a 27% decrease in carbon stored in forests. The conversion of forestland to cropland, while increasing carbon stocks in agricultural areas, has not compensated for the total carbon loss in the basin. As a result, the region's overall carbon stock has declined by 15%, highlighting the environmental cost of land use changes. This underscores the trade-offs between expanding agricultural land to meet growing food demands and the need to maintain carbon storage capacities to mitigate climate change. Field measurements are the most accurate way to estimate carbon stocks in terrestrial ecosystems, but they become less efficient and more expensive when applied to large areas. To address this challenge, the Enhanced Vegetation Index (EVI) tool was used for estimating carbon stocks effectively across various land use types. EVI is a reliable and cost-effective method for carbon stock estimation across landscapes. The strong correlation between EVI values and carbon stocks ($r^2 = 0.515$, $r = 0.72$) shows that EVI can reliably predict the carbon content in ecosystems, making it a valuable tool for large-scale environmental monitoring and carbon accounting. This can be particularly useful in regions like the Upper Awash River Basin, where land use changes are frequent and difficult to track using traditional methods.

The basin has experienced a notable decline in the ESV over the past three decades, with a reduction of $227.54 million (13.14%) in total ESV. The primary losses have been in regulating and supporting services, which are essential for maintaining environmental equilibrium & human welfare. The decline in ESV reflects the degradation of natural wealth due to LULC changes: forest degradation & deforestation, wetland shifts to cropland, and the expansion of built-up areas. The degree of inelasticity varies among different ecosystem services, reflecting their unique vulnerabilities to changes in ecosystem value coefficients. Importantly, each LULC category exhibited a sensitivity coefficient of less than one, suggesting that ESV is relatively inelastic, resulting in minimal fluctuations. Despite some fluctuations in specific services, the overall trend suggests that the basin's ecosystems are becoming less resilient and less capable of providing essential services.

This study provides valuable insights into LULC changes on ESV & carbon stocks, but it has limitations. These include reliance on RS data, which may be affected by cloud cover and sensor issues, and the assumption of constant relationships between LULC & ESV, along with limited ground-truthing. This study not only contributes to the understanding of LULC impacts on services provided by the ecosystem in the basin but also presents a new methodological basis that can be useful to other regions facing the same ecological problems. By integrating remote sensing, ArcGIS, the InVEST model, and regression analysis, this study demonstrates a comprehensive method for evaluating LULC changes & their consequences on carbon stock dynamics & ecosystem service values. A key innovation of these findings is the use of the EVI as a cost-effective and reliable tool for estimating carbon stocks across different land use types. The strong correlation between EVI and carbon stock measurements provides a scalable solution for large-area carbon monitoring, particularly in regions where traditional field-based methods may be less practical or too expensive. This combined approach, integrating multiple tools and methodologies, offers a robust framework that can support sustainable land management strategies and inform policy decisions in areas experiencing rapid land use changes.

6.2 RECOMMENDATIONS

- ✓ **Promote Sustainable Land Management Practices:** The ongoing transformation of the landscape in the Upper Awash River Basin presents serious challenges to the region's climate resilience. The loss of critical ecosystems, coupled with reduced carbon stocks and ecosystem services, makes the area more vulnerable to the impacts of climate change, namely, floods, droughts, & loss of biodiversity. Thus, this study emphasizes the need for a balanced approach to sustainable land management practice that accommodates both the demand for agricultural expansion and the necessity to protect and restore vital ecosystems. Given the significant losses in forest cover and wetlands, immediate action is needed to strengthen conservation and restoration programs. Community-based forest management, reforestation, and wetland rehabilitation initiatives can help restore carbon stocks and ecosystem services.
- ✓ **Further research is needed to compare the ESV between the locally calibrated coefficients and the global value coefficient**

  The coefficient of sensitivity was inelastic, and the methods used were reliable and robust to estimate the overall ESV in the Upper Awash River Basin. However, due to the limitation of global coefficient values, further research is needed to compare these findings with locally calibrated coefficients.
- ✓ **Develop Incentives for Ecosystem Service Preservation:** Introduce economic incentives such as payments for ecosystem services (PES) to encourage landholders and communities to maintain and enhance ecosystem functions, especially regulating and supporting services that have seen the greatest decline.
- ✓ **Promote the use of tools like the Enhanced Vegetation Index (EVI)** for estimating carbon stock at the landscape level, particularly in areas with limited data and expand this approach to other areas for better global conservation strategies. It captures variations in vegetation health, enabling efficient and cost-effective monitoring, and improving global conservation strategies and carbon stock assessments. However, additional research using Sentinel imagery is needed to compare results with those from Landsat data, ensuring more accurate carbon stock estimation

  To effectively address these gaps and drive implementation, the Ministry of Planning and Development and the Environmental Protection Authority should integrate climate resilience and ecosystem service monitoring into national development plans. The Ministry of Agriculture should promote sustainable land management and reforestation. The Ethiopian Forestry Development should support community-based forest management and expand monitoring systems. Academic institutions should research EVI calibration and landscape carbon dynamics. Local organizations should create awareness and participate in grassroots planning.

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APPENDIX: SUPPLEMENTARY MATERIALS

APPENDIX 1. GROUND CONTROL POINT DATA SHEETS

LULC Ground survey

Date_________________________ Zone ____________________ District Name____________________ Kebele ____________________

Code	GCP coordination			Type of LULC
	Latitude	Longitude	Altitude (m)	

Code, Built-up =1, High Forest =2, Shrubland =3, Wetland = 4, Cropland = 5,

APPENDIX 2. QUESTIONNAIRE CHECKLIST FOR HOUSEHOLDS (HHS)

Questionnaire code: _______________ Name of the interviewer ___________________Name of Interviewed________________ Survey Area: District: ___________ Kebele: _________ Village: ________ Date of interview: Day: _______ Month ________ Year: __________ Land hold size you have___________________

1. How long have you been in this place? _________

2. Is there any Land Use and Land Cover Change happening in your area?

   A) Yes____ B) NO_____

3. If yes, which Land Use and Land Cover (LULC) categories have changed most rapidly between 1993 and 2023, and how can they be ranked?

A. Forest land___________

B. Agricultural land__________

C. Wetland_____________

D. Shrubland _______________

E. Built-up______________

F. Others_____________________

4. If there is a change, which types of land have increased or decreased over this period? Rank it. Decrease=1 Increase =2 No change =0

LULC classes	Years			
	1993	2003	2013	2023
Built-up				
High forest				
Shrubland				
Wetland				
Cropland				
other				

5. If there is a LULCC (decrease/increase), what do you think are the main drivers (both proximate and underlying)? Please rank them in order of importance

A. Agricultural Expansion__________

B. Tenure__________

C. Infrastructure/settlement___________

D. Population density________________

E. Wood extraction for firewood, charcoal, and construction ___________

F. Poverty___________

G. Others____________

APPENDIX 3. QUESTIONNAIRE CHECKLIST FOCUS GROUP DISCUSSION (FDG)

Region: ________, Zone: _______, District: __________

Name of rural Kebele ____________ No. of participants__________

Date______________

1. What does Land Use and Land Cover look like in your area?

2. Is the land use and land cover in your area undergoing an increase or decrease?

3. Which Land Use and Land Cover categories are increasing or decreasing the most rapidly? Please list and rank them

4. During which period did Land Use and Land Cover change occur most rapidly?
   A. 1993, B. 2003, C. 2013, D. 2023

5. What are the direct and indirect drivers of Land Use and Land Cover Change?

APPENDIX 4. QUESTIONNAIRE CHECKLIST FOR KEY INFORMANT INTERVIEW (KII)

Questionnaire code: ________________

Name of the interviewer ________________

Name of interviewed__________________

Survey Area: District: ____________ Kebele: __________

Date of interview: Day: _______ Month ________ Year: ___________

1. What are the existing land use management systems in your area?

2. Have you known any change in the LULC in your area over the past 30 years?

   A) Yes B) No

3. Which LULC have you observed and changed rapidly? Please rank

4. What is your opinion of the drivers (proximate and underlying) of LULCC in your area?

5. In your opinion, what do you think is the solution for the causes/drivers of the LULCC?

APPENDIX 5. CONFUSION MATRIX FOR THE CLASSIFICATION OF 1993

1993		**Reference data**						**Users Accuracy**
		BA	**HF**	**SL**	**WL**	**CL**	**Total**	
Classification data	**BA**	12				3	15	**80.00**
	HF		17	3		0	20	**85.00**
	SL		1	21	2	1	25	**84.00**
	WL			1	22	2	25	**88.00**
	CL	2		1	2	35	40	**87.50**
	Total	14	18	26	26	41	125	
Producer accuracy		85.71	94.44	80.8	84.6	85.37		**Overall accuracy = 85.6%**

APPENDIX 6. CONFUSION MATRIX FOR THE CLASSIFICATION OF 2003

2003		Reference data						Users Accuracy
		BA	HF	SL	WL	CL	Total	
Classification data	BA	12				3	15	**80.00**
	HF		18	2		0	20	**90.00**
	SL			22	2	1	25	**88.00**
	WL				23	2	25	**92.00**
	CL	2		1	1	36	40	**90.00**
	Total	14	18	25	26	42	125	
Producer accuracy		85.71	100.00	88.0	88.5	85.71		**Overall accuracy = 88.8%**

APPENDIX 7. CONFUSION MATRIX FOR THE CLASSIFICATION OF 2013

2013		Reference data						Users Accuracy
		BA	HF	SL	WL	CL	Total	
Classification data	BA	13				2	15	**86.67**
	HF		18	1		1	20	**90.00**
	SL		1	22	1	1	25	**88.00**
	WL			1	23	1	25	**92.00**
	CL	2		1	1	36	40	**90.00**
	Total	15	19	25	25	41	125	
Producer accuracy		86.67	94.74	88	92	87.80		**Overall accuracy = 89.6%**

APPENDIX 8. CONFUSION MATRIX FOR THE CLASSIFICATION OF 2013

2023		Reference data						Users Accuracy
		BA	HF	SL	WL	CL	Total	
Classification data	BA	13				2	15	**86.67**
	HF		18	2		0	20	**90.00**
	SL			23	1	1	25	**92.00**

2023		Reference data						Users Accuracy
		BA	HF	SL	WL	CL	Total	
	WL				24	1	25	**96.00**
	CL	2		1	2	37	40	**92.50**
	Total	15	18	26	27	41	125	
Producer accuracy		86.67	100.00	88.5	88.9	90.24		**Overall accuracy = 92%**

APPENDIX 9. FOREST CARBON STOCK AT DIFFERENT POOLS

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
1	404548	1000109	134.2323	63.08918	26.84646	12.61784	102.69	178.397
2	405244	1001308	145.3343	68.30712	29.06686	13.66142	102.05	184.0205
3	404886	1000732	76.6541	36.02743	15.33082	7.205485	103.32	146.5599
4	405011	1001756	37.51885	17.63386	7.50377	3.526772	88.053	109.2136
5	405328	1000758	134	62.98	26.8	12.596	126.34	201.911
6	405312	1001065	189	88.83	37.8	17.766	133.27	239.865
7	405594	1000422	231	108.57	46.2	21.714	95.452	225.736
8	405723	1000714	196	92.12	39.2	18.424	93.164	203.708
9	406077	1004850	445.2212	209.254	89.04424	41.85079	145.89	397.0008
10	406366	1004850	1876.518	881.9634	375.3036	176.3927	124.18	1182.537
11	406632	1004850	103.9886	48.87465	20.79772	9.774929	119.71	178.3546
12	406932	1004865	113.2024	53.20511	22.64047	10.64102	106.85	170.6971
13	407182	1004844	127.2341	59.80003	25.44682	11.96001	173.53	245.292
14	407192	1005212	140.3211	65.95092	28.06422	13.19018	123.67	202.8071
15	406994	1005230	115.4544	54.26357	23.09088	10.85271	102.72	167.8383
16	406693	1005233	125.7612	59.10776	25.15224	11.82155	120.87	191.7983
17	406440	1005233	129.0912	60.67286	25.81824	12.13457	162.93	235.7384
18	406103	1002990	368.2378	173.0717	73.64755	34.61435	70.168	277.854
19	406353	1002967	353.0281	165.9232	70.60561	33.18464	87.841	286.9489
20	406667	1002962	460.7641	216.5591	92.15283	43.31183	87.846	347.7174
21	406930	1002999	215.1787	101.134	43.03573	20.22679	75.973	197.3343
22	406995	1003360	285.9397	134.3916	57.18794	26.87833	97.246	258.5159
23	406737	1003389	405.9626	190.8024	81.19251	38.16048	209.58	438.5425
24	406469	1003354	326.5622	153.4842	65.31244	30.69685	101.53	285.7116
25	406524	1003911	395.6434	185.9524	79.12869	37.19048	96.454	319.5972

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
26	406772	1003681	292.8741	137.6508	58.57482	27.53016	112.06	277.2453
27	407045	1003929	348.2542	163.6795	69.65084	32.7359	101.24	297.665
28	407030	1003655	171.6465	80.67387	34.32931	16.13477	81.316	178.1249
29	407294	1004298	356.7831	167.6881	71.35662	33.53761	127.99	329.2162
30	407023	1004324	645.8602	303.5543	129.172	60.71086	102.37	466.6391
31	406997	1004310	292.67	137.5549	58.53401	27.51098	59.241	224.3071
32	404039	1003555	217.1121	102.0427	43.42242	20.40854	129.37	251.8219
33	404039	1003807	223.5512	105.0691	44.71024	21.01381	152.61	278.7011
34	404034	1004309	267.3212	125.641	53.46424	25.12819	127.53	278.3051
35	403681	1004311	287.3356	135.0477	57.46712	27.00955	136.61	298.6681
36	403680	1004066	293.1123	137.7628	58.62246	27.55256	147.94	313.262
37	403679	1003818	186.4553	87.63399	37.29106	17.5268	22.582	127.7429
38	403332	1004181	112.8231	53.02684	22.56461	10.60537	134.14	197.7812
39	403323	1004434	216.7894	101.891	43.35788	20.3782	120.31	242.5797
40	402583	1004151	242.8411	114.1353	48.56823	22.82707	72.846	209.8093
41	409133	1002928	180.7996	84.97583	36.15993	16.99517	131.19	233.17
42	408766	1002697	248.3114	116.7063	49.66227	23.34127	190.25	330.3066
43	409352	1003608	172.1875	80.92814	34.4375	16.18563	107.83	204.9458
44	409623	1003403	287.2194	134.9931	57.44388	26.99862	207.19	369.1877
45	409507	1003519	281.7207	132.4087	56.34414	26.48174	117.60	276.4955
46	409508	1003817	175.7699	82.61186	35.15399	16.52237	80.997	180.1312
47	409509	1004115	179.6952	84.45673	35.93903	16.89135	74.249	175.5971
48	409908	1004164	250.6714	117.8156	50.13428	23.56311	81.731	223.1097
49	409908	1003866	150.287	70.6351	30.0574	14.1270	87.33	172.092
50	409907	1003568	187.570	88.1579	37.5140	17.6315	91.98	197.769
51	409906	1003270	182.110	85.5919	36.4221	17.1183	74.386	177.096
52	410258	1003364	167.541	78.7445	33.5083	15.7489	105.60	200.097
53	410306	1003485	115.673	54.3667	23.1347	10.8733	177.08	242.324
54	410306	1003484	132.453	62.2530	26.4906	12.4506	105.09	179.800
55	410655	1003236	188.122	88.4174	37.6244	17.6835	98.029	204.13
56	410665	1002998	132.298	62.1804	26.4597	12.4360	86.469	161.085
57	408768	1002444	155.877	73.2623	31.1754	14.6524	107.87	195.788
58	408429	1002947	173.804	81.6881	34.7609	16.3376	187.34	285.367
59	408090	1003196	172.761	81.1980	34.5523	16.2396	114.69	212.133
60	406791	1000127	187	87.89	37.4	17.578	109.33	214.805

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
61	449158	990709	374.08	187.04	74.816	37.408	98	322.448
62	449003	989297	254.657	127.328	50.9314	25.4657	107	259.794
63	449949	988835	314.64	157.32	62.928	31.464	110	298.784
64	450622	989356	22.24	11.12	4.448	2.224	147	160.344
65	451600	989938	504.32	252.16	100.864	50.432	115	417.592
66	452309	990567	1096.4	548.2	219.28	109.64	82	739.84
67	452731	990981	176.305	88.1525	35.261	17.6305	47	152.783
68	452060	991995	50.08	25.04	10.016	5.008	79	109.048
69	451419	991935	396.195	198.097	79.239	39.6195	96	333.717
70	450716	991874	56.12	28.06	11.224	5.612	109	142.672
71	450350	991445	234.84	117.42	46.968	23.484	139	279.904
72	449403	991169	203.44	101.72	40.688	20.344	128	250.064
73	448669	990863	325.8	162.9	65.16	32.58	99	294.48
74	448149	990096	50.504	25.252	10.1008	5.0504	81	111.302
75	449035	990464	165.84	82.92	33.168	16.584	87	186.504
76	450655	991721	47.24	23.62	9.448	4.724	129	157.344
77	451236	992610	305.84	152.92	61.168	30.584	155	338.504
78	451206	992887	145.44	72.72	29.088	14.544	138	225.264
79	451299	993654	218	109	43.6	21.8	130	260.8
80	451544	994023	13.468	6.734	2.6936	1.3468	88	96.0808
81	451330	994545	177.4	88.7	35.48	17.74	158	264.44
82	450965	995129	123.44	61.72	24.688	12.344	129	203.064
83	450721	995590	22.12	11.06	4.424	2.212	127	140.272
84	450202	995314	115.6	57.8	23.12	11.56	101	170.36
85	450140	995007	155.64	77.82	31.128	15.564	103	196.384
86	449886	994943	741.912	370.956	148.382	74.1912	100	545.147
87	449981	989971	256.76	128.38	51.352	25.676	103	257.056
88	449438	991668	206.7	103.35	41.34	20.67	103	227.02
89	447719	991592	128.424	64.212	25.6848	12.8424	91	168.054
90	447822	992443	165.816	82.908	33.1632	16.5816	95	194.489
91	449495	992216	456.68	228.34	91.336	45.668	82.8	356.808
92	449795	992669	210.52	105.26	42.104	21.052	80.6	206.912
93	449930	993104	201.28	100.64	40.256	20.128	86	206.768
94	450270	993558	232	116	46.4	23.2	81.4	220.6
95	450685	993936	209.68	104.84	41.936	20.968	74	199.808

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
96	450780	994314	501.48	250.74	100.296	50.148	77.8	378.688
97	450326	994540	150.76	75.38	30.152	15.076	125	215.456
98	449911	994389	239.96	119.98	47.992	23.996	102	245.976
99	449665	994144	515.96	257.98	103.192	51.596	103	412.576
100	449400	993709	163.8	81.9	32.76	16.38	97	195.28
101	449060	993236	22.52	11.26	4.504	2.252	94	107.512
102	448928	992783	73.4	36.7	14.68	7.34	110	154.04
103	448531	992197	176.96	88.48	35.392	17.696	122	228.176
104	452212	994677	355.16	177.58	71.032	35.516	103	316.096
105	452475	993887	323.36	161.68	64.672	32.336	100	294.016
106	451685	995286	176.72	88.36	35.344	17.672	126	232.032
107	453068	995056	425.48	212.74	85.096	42.548	128	383.288
108	453808	994710	567.12	283.56	113.424	56.712	128	468.272
109	448456	991630	211.88	105.94	42.376	21.188	114	241.128
110	448243	992776	157.44	78.72	31.488	15.744	92	186.464
111	449555	990960	98.92	49.46	19.784	9.892	88	147.352
112	449005	990746	108.48	54.24	21.696	10.848	73	138.088
113	449249	990285	121.84	60.92	24.368	12.184	96	169.104
114	449799	990345	411.72	205.86	82.344	41.172	117	364.032
115	450226	990683	504.72	252.36	100.944	50.472	79	381.832
116	450991	991265	270.68	135.34	54.136	27.068	112	274.408
117	451479	991203	1032.52	516.26	206.504	103.252	87	706.512
118	451357	990989	329.96	164.98	65.992	32.996	96	293.976
119	450837	990897	607.08	303.54	121.416	60.708	124	488.248
120	448670	990921	607.08	303.54	121.416	60.708	124	488.248
121	449002	991067	190.745	89.6504	38.1491	17.9300	98	205.580
122	449026	991070	50.4630	23.7176	10.0926	4.74352	84	112.461
123	449185	990832	307.337	144.448	61.4675	28.8897	111	284.338
124	449800	990720	68.1724	32.0410	13.6345	6.40821	87	125.449
125	449841	990329	119.775	56.2944	23.9550	11.2588	95	162.553
			32260.1	**15657.6**	**6452.01**	**3131.53**	**13587.**	**32376.4**
			258.081	**125.26**	**51.616**	**25.0526**	**108.69**	**259.011**

APPENDIX 10. SHRUBLAND CARBON STOCK AT DIFFERENT POOLS

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
1	404212	1000242	56.4532	26.533	11.29064	5.306601	101.504	133.3436
2	403319	1004692	220.1213	103.457	44.02426	20.6914	162.1002	286.2486
3	402464	1004167	197.8792	93.00322	39.57584	18.60064	58.4028	170.0067
4	402788	1003924	173.9405	81.75203	34.7881	16.35041	144.4938	242.5962
5	402766	1004136	183.3715	86.1846	36.6743	17.23692	101.0627	204.4842
6	403250	1004064	234.4332	110.1836	46.88664	22.03672	123.0723	255.2926
7	402956	1004628	207.5963	97.57027	41.51926	19.51405	173.5332	290.6175
8	404040	1004058	192.2312	90.34866	38.44624	18.06973	121.2456	229.664
9	404718	1002398	189.3241	88.98233	37.86482	17.79647	74.35	181.1288
10	404920	1002269	167.111	78.54217	33.4222	15.70843	93.947	188.1976
11	404596	1000443	65.889	30.96783	13.1778	6.193566	79.858	117.0194
12	404497	999764	64.2299	30.18805	12.84598	6.037611	101.64	137.8657
13	404835	1000368	144.4259	67.88019	28.88519	13.57604	145.237	226.6932
14	404796	999965	74.20309	34.87545	14.84062	6.975091	121.806	163.6565
15	404788	999665	25.81989	12.13535	5.163978	2.427069	98.106	112.6684
16	404788	999399	187.1123	87.94278	37.42246	17.58856	106.302	211.8333
17	404484	999534	112.3311	52.79562	22.46622	10.55912	89.644	152.9987
18	404252	999858	87.4455	41.09939	17.4891	8.219877	98.036	147.3553
19	405236	999758	51.67102	24.28538	10.3342	4.857076	137.295	166.4375
20	405218	1000057	63.31272	29.75698	12.66254	5.951395	105.138	140.8464
21	405245	1000356	34.8606	16.38448	6.97212	3.276896	95.14	114.8014
22	405599	1000127	37.15345	17.46212	7.43069	3.492424	151.787	172.7415
23	405626	999804	27.3456	12.85243	5.46912	2.570486	89.163	104.5859
24	405747	1001012	36.1121	16.97269	7.22242	3.394537	110.077	130.4442
25	406766	999798	148.45	69.7715	29.69	13.9543	150.07	233.7958
26	406798	999869	100.12	47.0564	20.024	9.41128	133.548	190.0157
27	406451	1000122	102.132	48.00204	20.4264	9.600408	104.387	161.9894
28	406445	1000373	126.34	59.3798	25.268	11.87596	105.988	177.2438
29	406798	1000371	85.674	40.26678	17.1348	8.053356	121.923	170.2431
30	408428	1002444	195.1123	91.70278	39.02246	18.34056	95.535	205.5783
31	408429	1002696	201.123	94.52781	40.2246	18.90556	42.837	156.2704
32	408767	1002945	170.6755	80.21749	34.1351	16.0435	87.007	183.268
33	409130	1002423	188.2637	88.48392	37.65273	17.69678	93.519	199.6997

Plot	x	y	AGB	AGC	BGB	BGC	SOC	Total
34	409132	1002677	127.8301	60.08014	25.56602	12.01603	93.64	165.7362
35	408439	1003195	179.604	84.4139	35.92081	16.88278	70.963	172.2597
36	409980	1003172	30.97068	14.55622	6.194135	2.911243	149.368	166.8355
37	410245	1003284	119.6657	56.24288	23.93314	11.24858	187.342	254.8335
38	448583	990390	8.974817	4.218164	1.794963	0.843633	99	104.0618
39	449056	991187	10.87934	5.113289	2.175868	1.022658	67	73.13595
40	448838	990011	15.3362	7.208013	3.067239	1.441603	76	84.64962
41	449120	989958	108.8084	51.13992	21.76167	10.22798	78	139.3679
42	448526	990069	27.44678	12.89999	5.489356	2.579997	84	99.47998
43	448031	989246	72.56	36.28	14.512	7.256	114	157.536
44	448002	991101	158.18	79.09	31.636	15.818	91	185.908
45	448058	990588	169.914	84.957	33.9828	16.9914	109	210.9484
46	447813	991989	237.76	118.88	47.552	23.776	85	227.656
47	449316	991094	52.00788	24.4437	10.40158	4.88874	78	107.3324
48	450109	990752	45.35928	21.31886	9.071855	4.263772	78	103.5826
49	449726	990200	35.05528	16.47598	7.011055	3.295196	89	108.7712
50	449432	990078	50.90032	23.92315	10.18006	4.784631	110	138.7078
			5603.51	**2652.80**	**1120.70**	**530.561**	**5277.06**	**8460.43**
			112.070	**53.05611**	**22.4140**	**10.6112**	**105.541**	**169.208**

APPENDIX 11. CROPLAND CARBON STOCK AT DIFFERENT POOLS

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
1	9.052409	38.24329	2830	28.3
2	8.926804	38.1129	8440	84.4
3	8.914631	38.10544	8420	84.2
4	8.900394	38.10847	6620	66.2
5	8.940725	38.23692	6310	63.1
6	9.097372	38.28104	1490	14.9
7	9.098957	38.25844	1470	14.7
8	9.112791	38.25018	3410	34.1
9	8.949031	38.24472	6310	63.1
10	9.092664	38.29236	2760	27.6
11	9.05033	38.28503	4410	44.1
12	8.96885	38.17123	5190	51.9
13	8.965374	38.23793	7720	77.2

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
14	8.937299	38.18159	6280	62.8
15	8.969691	38.12066	5500	55
16	8.955132	38.11744	6580	65.8
17	8.898853	38.11866	7770	77.7
18	8.958576	38.24123	6370	63.7
19	9.016751	38.21392	8540	85.4
20	9.008903	38.28604	5060	50.6
21	9.0242	38.12826	6370	63.7
22	9.052652	38.23747	4330	43.3
23	9.103715	38.26922	2180	21.8
24	9.065915	38.30949	4740	47.4
25	9.080217	38.26725	4100	41
26	9.098201	38.29122	2790	27.9
27	8.883152	38.0956	8190	81.9
28	8.927811	38.1217	6000	60
29	8.940863	38.11496	7300	73
30	9.014351	38.14744	7570	75.7
31	8.957871	38.17559	5020	50.2
32	8.980097	38.16545	6130	61.3
33	8.977242	38.15492	5190	51.9
34	8.972454	38.14548	4360	43.6
35	8.975417	38.12866	7780	77.8
36	9.142829	38.15436	1530	15.3
37	9.118915	38.14595	1580	15.8
38	9.099517	38.15443	3790	37.9
39	9.037863	38.15426	6950	69.5
40	9.091617	38.27668	4350	43.5
41	8.884239	38.4236	6968	69.68
42	8.876074	38.42096	6576	65.76
43	8.862631	38.41818	3873	38.73
44	9.065067	38.36704	3977	39.77
45	8.997345	38.44974	2410	24.1
46	8.983053	38.36782	6567	65.67
47	8.982723	38.39597	5840	58.4
48	8.979902	38.33838	4860	48.6
49	8.991195	38.39982	4782	47.82
50	8.99539	38.40083	4549	45.49
51	8.978457	38.37286	7289	72.89
52	8.97126	38.44005	6819	68.19
53	8.965006	38.31873	5962	59.62
54	8.958039	38.35013	5882	58.82

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
55	8.937506	38.3897	5921	59.21
56	8.936997	38.36957	6763	67.63
57	8.936803	38.25537	4767	47.67
58	8.910631	38.32853	4289	42.89
59	9.015812	38.33186	4886	48.86
60	8.987578	38.39636	7573	75.73
61	9.032844	38.34793	6618	66.18
62	9.03795	38.40977	4318	43.18
63	9.05351	38.42965	1570	15.7
64	8.98405	38.36611	7849	78.49
65	8.983411	38.32375	6068	60.68
66	9.101575	38.39925	1554	15.54
67	9.094911	38.3241	2428	24.28
68	9.082059	38.44919	1185	11.85
69	8.867541	38.40598	3982	39.82
70	8.890103	38.42148	5843	58.43
71	9.073659	38.44508	960	9.6
72	8.919097	38.32243	4065	40.65
73	8.964054	38.39352	8269	82.69
74	8.984966	38.42166	6567	65.67
75	8.986245	38.32204	6296	62.96
76	8.989614	38.36749	6529	65.29
77	9.012592	38.4171	5988	59.88
78	9.019189	38.43202	8066	80.66
79	9.034382	38.35243	4257	42.57
80	9.037087	38.32656	3829	38.29
81	9.070305	38.34316	3658	36.58
82	8.867416	38.41942	3995	39.95
83	8.893897	38.39742	6873	68.73
84	8.929708	38.32576	4424	44.24
85	8.940044	38.33783	4863	48.63
86	8.940162	38.25476	4142	41.42
87	8.949216	38.388	6528	65.28
88	8.996458	38.38927	4032	40.32
89	9.001714	38.40665	3656	36.56
90	9.033086	38.40403	2510	25.1
91	9.055058	38.43872	1423	14.23
92	9.058244	38.34168	3905	39.05
93	9.066521	38.4209	1678	16.78
94	9.07062	38.3645	5788	57.88
95	9.093313	38.41669	1065	10.65

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
96	8.862264	38.40284	4215	42.15
97	8.892834	38.38376	3969	39.69
98	8.901343	38.35058	5764	57.64
99	8.91635	38.30337	3759	37.59
100	8.91942	38.31014	4374	43.74
101	8.930188	38.36564	5007	50.07
102	9.075081	38.38152	4704	47.04
103	9.079824	38.34933	3067	30.67
104	9.083677	38.41107	1788	17.88
105	9.103216	38.36027	2276	22.76
106	9.105426	38.42112	1387	13.87
107	8.931351	38.30267	4970	49.7
108	8.942128	38.36634	6208	62.08
109	8.946247	38.31445	6765	67.65
110	8.990853	38.3842	5516	55.16
111	8.998872	38.36491	2796	27.96
112	9.004838	38.4207	2573	25.73
113	9.00967	38.4499	1641	16.41
114	9.025018	38.41478	2405	24.05
115	9.049787	38.36815	2931	29.31
116	9.056418	38.42792	1745	17.45
117	9.061049	38.40615	2662	26.62
118	9.062523	38.43081	1943	19.43
119	9.083658	38.34956	4588	45.88
120	8.954783	38.47088	2120	21.2
121	8.9452	38.48998	2270	22.7
122	9.136662	38.49722	1160	11.6
123	9.114389	38.47335	2740	27.4
124	9.035861	38.47061	1710	17.1
125	9.174656	38.44565	4430	44.3
126	8.97293	38.46798	1850	18.5
127	9.06622	38.51736	1850	18.5
128	9.2097	38.48274	6760	67.6
129	9.20397	38.47657	4320	43.2
130	9.02126	38.51422	1500	15
131	8.96387	38.51587	2480	24.8
132	8.93543	38.57908	1810	18.1
133	9.1843	38.48161	2740	27.4
134	9.121039	38.5618	1150	11.5
135	9.109214	38.49503	1960	19.6
136	9.177993	38.52381	3620	36.2

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
137	9.165317	38.53056	2070	20.7
138	8.913619	38.50303	2930	29.3
139	9.07041	38.56805	1720	17.2
140	9.01356	38.48912	3960	39.6
141	8.95529	38.48799	2980	29.8
142	8.91503	38.5283	8060	80.6
143	8.9993	38.51358	1840	18.4
144	9.11086	38.46373	1250	12.5
145	9.161018	38.45877	1220	12.2
146	9.14341	38.43247	1910	19.1
147	9.05658	38.46756	1350	13.5
148	8.957898	38.44152	6770	67.7
149	9.001792	38.46812	2390	23.9
150	9.05343	38.55393	2720	27.2
151	9.08251	38.47944	2480	24.8
152	9.10934	38.52355	1330	13.3
153	9.12285	38.44728	1520	15.2
154	9.15951	38.41579	3500	35
155	9.17303	38.46746	3410	34.1
156	9.09974	38.46476	2970	29.7
157	9.198573	38.47284	2780	27.8
158	8.97951	38.50939	1640	16.4
159	8.92922	38.40189	3050	30.5
160	9.015565	38.53502	2650	26.5
161	9.143985	38.5414	2160	21.6
162	9.136053	38.47261	3370	33.7
163	8.935317	38.41412	3820	38.2
164	8.901514	38.44818	4800	48
165	9.03907	38.48356	1930	19.3
166	9.08954	38.53167	1770	17.7
167	9.14896	38.45266	3120	31.2
168	9.19396	38.48376	5060	50.6
169	9.200698	38.48392	5170	51.7
170	9.15714	38.46351	2760	27.6
171	8.94884	38.52311	2290	22.9
172	9.158537	38.51129	3100	31
173	9.148012	38.48054	3730	37.3
174	9.106211	38.54734	1390	13.9
175	8.95351	38.50474	1870	18.7
176	9.06122	38.52683	3010	30.1
177	9.137229	38.55732	921	9.21

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
178	8.810611	38.25865	4929.52	49.3
179	8.918899	38.12221	3421.37	34.21
180	8.932257	38.16293	4293.39	42.93
181	8.769039	38.02834	1497.77	14.98
182	8.891875	38.14914	4999.32	49.99
183	8.783127	38.06796	1917.28	19.17
184	8.851105	38.13608	3366.91	33.67
185	8.715797	38.02716	1263.56	12.64
186	8.83689	38.1505	4099.85	41
187	8.715267	38.05449	1953.56	19.54
188	8.767855	38.10964	8174.72	81.75
189	8.85082	38.21813	3880.15	38.8
190	8.837647	38.23233	3431.83	34.32
191	8.729045	38.14998	4430.2	44.3
192	8.742807	38.16322	4655.67	46.56
193	8.742324	38.19093	4347.02	43.47
194	8.770324	38.21797	4456.58	44.57
195	8.798066	38.24521	5148.01	51.48
196	8.796897	38.16348	4928.48	49.28
197	8.769669	38.19145	5604.19	56.04
198	8.796338	38.08105	4795.13	47.95
199	8.809789	38.04137	2235.84	22.36
200	8.905399	38.13593	4467.44	44.67
201	8.919068	38.17696	5393.87	53.94
202	8.728715	38.04098	1720.09	17.2
203	8.783141	38.09533	10150.9	101.51
204	8.797875	38.10898	12284.3	122.84
205	8.878353	38.19056	4722.07	47.22
206	8.851203	38.19062	3105.08	31.05
207	8.756468	38.15016	6071.36	60.71
208	8.878695	38.16307	4552.09	45.52
209	8.89181	38.17674	5574.77	55.75
210	8.756872	38.12241	7518.17	75.18
211	8.796944	38.19077	6453.28	64.53
212	8.932322	38.13589	2786.4	27.86
213	8.796859	38.0273	1607.63	16.08
214	8.822506	38.05689	1552.22	15.52
215	8.824264	38.08152	1984.33	19.84
216	8.877593	38.13628	5447.54	54.48
217	8.905721	38.19023	3496.03	34.96
218	8.756425	38.06866	3546.97	35.47

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
219	8.769913	38.08085	4319.02	43.19
220	8.810375	38.12255	7559.59	75.6
221	8.849262	38.16233	4269.06	42.69
222	8.783653	38.12235	8996.77	89.97
223	8.81044	38.14985	6860.3	68.6
224	8.878369	38.21786	3862.75	38.63
225	8.769747	38.13637	4101.54	41.02
226	8.837534	38.2042	5151.42	51.51
227	8.755485	38.17714	5218.21	52.18
228	8.810616	38.23166	4563.92	45.64
229	8.702017	38.14991	3991.41	39.91
230	8.715338	38.16363	4471.45	44.71
231	8.728575	38.17684	6777.14	67.77
232	8.756413	38.23162	10931	109.31
233	8.797008	38.21806	5027.7	50.28
234	8.741653	38.05413	2148.72	21.49
235	8.864778	38.17692	4770.25	47.7
236	8.796817	38.1362	5312.76	53.13
237	8.701213	38.17732	4699.52	47
238	8.782984	38.17693	4027.44	40.27
239	8.769712	38.16351	5323.13	53.23
240	8.742583	38.13629	5146.13	51.46
241	8.822531	38.21879	3525.94	35.26
242	8.851593	38.24571	2751.5	27.52
243	8.783379	38.20444	5340.07	53.4
244	8.864871	38.23154	5709.68	57.1
245	8.824155	38.24523	5205.76	52.06
246	8.742995	38.10925	8541.06	85.41
247	8.742896	38.21816	5371	53.71
248	8.919111	38.14962	5061.48	50.61
249	8.796737	38.05447	881.061	8.81
250	8.810092	38.06811	1470.83	14.71
251	8.905716	38.16266	5316.4	53.16
252	8.783337	38.1499	5017.93	50.18
253	8.758016	38.04089	1277.06	12.77
254	8.772439	38.05392	1496.76	14.97
255	8.810226	38.09515	5697.53	56.98
256	8.824125	38.10896	3081.89	30.82
257	8.864698	38.14966	7615.7	76.16
258	8.836372	38.42962	5484	54.84
259	8.833463	38.45429	5752	57.52

Plot no	Latitude	Longitude	C/gc3	Carbon (ton/ha)
260	8.852933	38.45569	7100	71
Total				11148.5
Total (ton/ha)				42.88

APPENDIX 12. WETLAND CARBON STOCK AT DIFFERENT POOLS

Plot no	X-coordinate	Y-coordinate	SOC (t/ha)
1	428105	1008974	87.231
2	435645	1016117	81.12
3	435169	1015641	74.871
4	437114	1014451	71.434
5	436796	1014371	77.342
6	436796	1014371	77.11
7	436518	1013300	63.123
8	432391	1026317	96.211
9	432827	1026317	88.111
10	432907	1025960	85.114
11	433423	1025801	90.112
12	433661	1024690	82.22
13	439098	1006672	76.781
14	438622	1006592	70.012
15	438463	1006335	66.99
16	445170	1003933	57.023
17	444972	1004092	58.992
18	444863	1003990	65.22
19	444995	1004122	73.09
20	445167	1004036	74.761
21	445246	1003844	80.254
22	445154	1004367	74.075
23	445352	1004512	65.001
24	445590	1004631	56.11
25	445610	1004512	62.332
26	445498	1004267	67.09
27	445637	1004248	66.01
28	401989	998140	54.989
29	402036	998140	62.91
30	401854	998132	59.075
31	401036	997997	58.11
32	400883	998037	60.114
33	401640	997458	53.178

Plot no	X-coordinate	Y-coordinate	SOC (t/ha)
34	401560	997410	66.93
35	401481	997386	62.033
36	400711	996600	60.087
37	400711	996569	52.001
38	386470	960645	82.91
39	394566	961888	87.98
40	394883	962259	85.02
41	395201	962285	81.005
42	395438	962497	78.221
43	395889	963185	77.111
44	394936	963952	63.006
45	394460	965116	82.022
46	394619	965249	90.21
47	394778	965592	96.09
48	394592	965884	87.21
49	391947	966862	93.44
50	392079	967497	95.11
51	392661	968053	92.211
52	392105	968794	93.332
53	391523	969376	76.003
54	390729	969667	63.434
55	390597	967233	98.11
56	389803	967312	97.11
57	390412	968212	93.22
58	389618	965804	85.45
59	394513	969270	89.08
60	394301	969746	92.09
61	394566	970090	91.12
62	394407	970408	92.22
63	394143	970448	76.118

APPENDIX 13. VALUE OF ECOSYSTEM FUNCTIONS FOR 1993

Ecosystem service	**Estimated Value of Ecosystem functions (US$ in million)**					
	1993					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Provisioning Services						
Food production	1.46	5.58	11.85	522.91	0.00	541.80

Ecosystem service	**Estimated Value of Ecosystem functions (US$ in million)**					
	1993					
Water supply	0.2	0.75	7.87	90.04	0.00	98.87
Raw materials	0.61	2.34	10.40	49.30	0.00	62.65
Genetic resources	11.15	42.60	1.91	234.55	0.00	290.22
Regulating services						
Water regulation	0.06	0.22	108.20	0.00	0.05	108.53
Waste treatment	0.88	3.35	58.19	89.36	0.00	151.78
Erosion control	2.46	9.40	50.32	24.09	0.00	86.26
Climate regulation	14.92	57.03	9.42	92.52	2.81	176.69
Biological control	0.08	0.31	18.30	7.43	0.00	26.11
Gas regulation	0.09	0.33	0.00	0.00	0.00	0.42
Disturbance regulation	0.48	1.84	57.63	0.00	0.00	59.95
Supporting Services						
Nutrient cycling	0.02	0.08	33.06	0.00	0.00	33.16
Pollination	0.22	0.84	0.00	4.95	0.00	6.01
Soil formation	0.1	0.39	0.00	119.75	0.00	120.24
Habitat/refuge	0.28	1.09	47.38	0.00	0.00	48.75
Cultural services						
Recreation	6.33	24.19	42.67	18.46	17.79	109.44
Cultural	0.01	0.06	38.45	0.00	0.00	38.51
Sum	39.35	150.41	495.64	1253.36	20.65	1959.41

APPENDIX 14. VALUE OF ECOSYSTEM FUNCTIONS FOR 2003

Ecosystem service	**Estimated Value of Ecosystem functions (US$ in million)**					
	2003					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Provisioning Services						
Food production	1.28	4.82	10.38	535.45	0.00	551.93
Water supply	0.17	0.65	6.90	92.20	0.00	99.92
Raw materials	0.54	2.02	9.11	50.48	0.00	62.15
Genetic resources	9.77	36.80	1.67	240.18	0.00	288.43

Ecosystem service	Estimated Value of Ecosystem functions (US$ in million)					
	2003					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Regulating services						
Water regulation	0.05	0.19	94.74	0.00	0.08	95.06
Waste treatment	0.77	2.89	50.95	91.51	0.00	146.12
Erosion control	2.16	8.12	44.06	24.66	0.00	79.00
Climate regulation	13.08	49.26	8.25	94.74	4.34	169.67
Biological control	0.07	0.27	16.02	7.61	0.00	23.96
Gas regulation	0.08	0.29	0.00	0.00	0.00	0.37
Disturbance regulation	0.42	1.59	50.46	0.00	0.00	52.48
Supporting Services						
Nutrient cycling	0.02	0.07	28.95	0.00	0.00	29.04
Pollination	0.19	0.72	0.00	5.07	0.00	5.99
Soil formation	0.09	0.34	0.00	122.63	0.00	123.05
Habitat/refuge	0.25	0.94	41.49	0.00	0.00	42.68
Cultural services						
Recreation	5.55	20.89	37.37	18.90	27.55	110.26
Cultural	0.01	0.05	33.66	0.00	0.00	33.73
Sum	34.50	129.92	434.01	1,283.42	31.97	1913.83

Appendix 15. Value of Ecosystem Functions for 2013

Ecosystem service	Estimated Value of Ecosystem functions (US$ in million)					
	2013					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Provisioning Services						

Ecosystem service	**Estimated Value of Ecosystem functions (US$ in million)**					
	2013					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Food production	1.16	3.28	8.84	555.66	0.00	568.94
Water supply	0.16	0.44	5.88	95.68	0.00	102.15
Raw materials	0.49	1.38	7.76	52.38	0.00	62.01
Genetic resources	8.86	25.04	1.43	249.25	0.00	284.57
Regulating services						
Water regulation	0.05	0.13	80.73	0.00	0.11	81.01
Waste treatment	0.70	1.97	43.42	94.96	0.00	141.04
Erosion control	1.95	5.53	37.54	25.59	0.00	70.62
Climate regulation	11.86	33.52	7.03	98.31	6.24	156.96
Biological control	0.06	0.18	13.65	7.89	0.00	21.79
Gas regulation	0.07	0.20	0.00	0.00	0.00	0.27
Disturbance regulation	0.38	1.08	43.00	0.00	0.00	44.46
Supporting Services						
Nutrient cycling	0.02	0.05	24.67	0.00	0.00	24.73
Pollination	0.17	0.49	0.00	5.26	0.00	5.93
Soil formation	0.08	0.23	0.00	127.25	0.00	127.57
Habitat/refuge	0.23	0.64	35.35	0.00	0.00	36.22
Cultural services						
Recreation	5.03	14.22	31.84	19.61	39.61	110.31
Cultural	0.01	0.03	28.68	0.00	0.00	28.73
Sum	31.27	88.41	369.81	1,331.87	45.96	1867.31

APPENDIX 16. VALUE OF ECOSYSTEM FUNCTIONS FOR 2023

Ecosystem service	**Estimated Value of Ecosystem functions (US$ in million)**					
	2023					
	Forest	**Shrubland**	**Wetland**	**Cropland**	**Built-up**	**Total**
Provisioning Services						
Food production	1.06	3.26	4.67	570.53	0.00	579.52
Water supply	0.14	0.44	3.10	98.24	0.00	101.92

Ecosystem service	Estimated Value of Ecosystem functions (US$ in million)					
	2023					
	Forest	Shrubland	Wetland	Cropland	Built-up	Total
Raw materials	0.45	1.37	4.10	53.79	0.00	59.70
Genetic resources	8.09	24.89	0.75	255.92	0.00	289.65
Regulating services						
Water regulation	0.04	0.13	42.61	0.00	0.13	42.90
Waste treatment	0.64	1.96	22.91	97.50	0.00	123.01
Erosion control	1.79	5.49	19.81	26.28	0.00	53.37
Climate regulation	10.83	33.32	3.71	100.94	7.15	155.95
Biological control	0.06	0.18	7.20	8.10	0.00	15.55
Gas regulation	0.06	0.20	0.00	0.00	0.00	0.26
Disturbance regulation	0.35	1.08	22.69	0.00	0.00	24.12
Supporting Services						
Nutrient cycling	0.02	0.05	13.02	0.00	0.00	13.08
Pollination	0.16	0.49	0.00	5.40	0.00	6.05
Soil formation	0.07	0.23	0.00	130.66	0.00	130.96
Habitat/refuge	0.21	0.64	18.66	0.00	0.00	19.50
Cultural services						
Recreation	4.60	14.13	16.80	20.14	45.35	101.02
Cultural	0.01	0.03	15.14	0.00	0.00	15.18
Sum	28.57	87.87	195.18	1,367.50	52.62	1731.74

APPENDIX 17. VALUE OF ECOSYSTEM FUNCTIONS AND CHANGES

Ecosystem service	Estimated Value of Ecosystem functions (US$ in million)				Total	Value of Ecosystem functions			
						Changes			
	1993	2003	2013	2023		1993-2003	2003-2013	2013-2023	1993-2023
Provisioning Services									
Food production	541.8	551.93	568.94	579.52	2242.19	10.13	17.01	10.58	37.72
Water supply	98.87	99.92	102.15	101.92	402.86	1.05	2.23	-0.23	3.05
Raw materials	62.65	62.15	62.01	59.7	246.51	-0.5	-0.14	-2.31	-2.95

Ecosystem service	Estimated Value of Ecosystem functions (US$ in million)				Total	Value of Ecosystem functions Changes			
	1993	2003	2013	2023		1993-2003	2003-2013	2013-2023	1993-2023
Genetic resources	290.22	288.43	284.57	289.65	1152.87	-1.79	-3.86	5.08	-0.57
Regulating services									
Water regulation	108.53	95.06	81.01	42.9	327.5	-13.47	-14.05	-38.11	-65.63
Waste treatment	151.78	146.12	141.04	123.01	561.95	-5.66	-5.08	-18.03	-28.77
Erosion control	86.26	79	70.62	53.37	289.25	-7.26	-8.38	-17.25	-32.89
Climate regulation	176.69	169.67	156.96	155.95	659.27	-7.02	-12.71	-1.01	-20.74
Biological control	26.11	23.96	21.79	15.55	87.41	-2.15	-2.17	-6.24	-10.56
Gas regulation	0.42	0.37	0.27	0.26	1.32	-0.05	-0.1	-0.01	-0.16
Disturbance regulation	59.95	52.48	44.46	24.12	181.01	-7.47	-8.02	-20.34	-35.83
Supporting Services									
Nutrient cycling	33.16	29.04	24.73	13.08	100.01	-4.12	-4.31	-11.65	-20.08
Pollination	6.01	5.99	5.93	6.05	23.98	-0.02	-0.06	0.12	0.04
Soil formation	120.24	123.05	127.57	130.96	501.82	2.81	4.52	3.39	10.72
Habitat/refuge	48.75	42.68	36.22	19.5	147.15	-6.07	-6.46	-16.72	-29.25
Cultural services									
Recreation	109.44	110.26	110.31	101.02	431.03	0.82	0.05	-9.29	-8.42
Cultural	38.51	33.73	28.73	15.18	116.15	-4.78	-5	-13.55	-23.33
Sum	1959.41	1913.83	1867.31	1731.74	7472.28	-45.58	-46.52	-135.57	-227.67

APPENDIX 18. LOCAL COMMUNITY CONSULTATION

Zone South West Shoa

District: Sebeta Hawas **Kebele:** Dembal Kejima

LKK	Maqaa Jirattotaa		saala	Zoonii	Mallattoo
1	Daagafaa	Dhaabaa	Dh	Gosaree fi Colloo	
2	Wandimmuu	Deesoo	''	Liluu fi Boree	
3	Hayiluu	Gubbisaa	''	Gosaree fi Collo	
4	Fiqaaduu	Abiidisaa	''	Liluu fi Boree	
5	Gammadaa	Bayyuu	''	Gosaree fi Colloo	
6	Hirgorchaa	Hajiru	''	Liluu fi Boree	
7	Tafaraa	Nagaasaa	''	Gosaree	
8	Tafaraa	Alamuu	''	Gosaree	
9	Mikkaksaa	Ilaalaa	''	Gosaree	
10	Bololchaa	Dibabaa	''	Gosaree	
11	Nagasaa	Bayyu	''	Gosaree	
12	Dadhi	Tadasaa	''	Gosaree	
13	Shoree	Wasii	''	Gosaree	
14	Girimaa	Dumichaa	''	Gosaree	
15	Marfaa	Dibaabaa	''	Gosaree	
16	Lammaa	Nagasaa	''	Alaboo	
17	Tasamaa	Girmaa	''	Chobii	
18	Dajane	Dame	''	Gosaree	
19	Bojaa	Nonoochaa	''	Boree Gosaree	
20	Aboraa	Colliqaa	''	Gosaree	
21	Badhaadhaa	Kisi	''	Liluu fi Boree	
22	Horsaa	Tadalaa	''	Gosaree	
23	Waqjiraa	Lelisaa	''	Liluu fi Boo	
24	Gabisaa	Shiferaa	''	Liluu fi Boo	
25	Suyumee	Dibabaa	''	Gosaree	
26	Adane	Waqjii	''	Boree	
27	Dannaa	Dandanaa	''	Liluu fi Boree	
28	Dabasaa	Anfasaa	''	Liluu fi Boo	
29	Lammi	Bacaa	''	Liluu fi Boo	
30	Alamu	Gabisaa	''	Gosaree	
31	Arjamaa	Damanaa	''	Gosaree fi Colloo	
32	Dibaabaa	Galanaa	''	Liluu fi Boree	
33	Maqarsaa	Bosisaa		Liluu fi Boo	

Zone South West Shoa

District: Becho **Kebele:** Deka Guda

#	Full Name	Sex	Zone	Woreda	Kebele	Signature of consent
1	Midhaksaa Gammadaa	M	[illegible]	Becho	Dh/Guda	[illegible]
2	Illiiqaa Bashuu Abarraa	"	"	"	"	Illiqaa
3	Lataa Agaa Jimaa	"	"	"	"	[illegible]
4	Jituu Bayisaa Dandanaa	F	"	"	"	[illegible]
5	Laggasaa Badhaasaa Dame	M	"	"	"	[illegible]
6	Adaanuu Waami Dubai	F	"	"	"	Adanu
7	Taddasaa Cibsaa Gudinaa	M	"	"	"	[illegible]
8	Leensaa Badhadhaa	F	"	"	"	[illegible]
9	Qaalbeshaa Baayisaa	M	"	"	"	[illegible]
10	Kumsaa Nagaraa	M	"	"	"	[illegible]
11	Magaa Raggaasaa	M	"	"	"	[illegible]
12	Mul'ataa Gammadaa	M	"	"	"	[illegible]
13	Dharmaa Sokbagaa	F	"	"	"	[illegible]
14	Dirribaa Waqgtolaa	M	"	"	"	[illegible]
15	Fayyisaa Ayyaanaa	M	"	"	"	[illegible]
16	Gurracamii Dhaabbaa	F	"	"	"	[illegible]
17	Eliyas Abarraa Aragaaw	M	"	"	"	[illegible]
18	Marii Bayyanaa	F	"	"	"	[illegible]
19	Addunyaa Midhaksaa	M	"	"	"	[illegible]
20	Korree Dabal Badhaanaa	F	"	"	"	[illegible]
21	Tarrafaa Maraciil	M	"	"	"	[illegible]
22	Gumaarii Itichaa	F	"	"	"	[illegible]
23	Dharmaa Taddasaa	F	"	"	"	Dhara
24	Sukkaree Tashoomaa	F	"	"	"	[illegible]
25	Haayilee Nagaraa	M	"	"	"	[illegible]
26	Birqii Gurmessaa	F	"	"	"	[illegible]
27	Lelloo Dandanaa	F	"	"	"	[illegible]
28	Taddasaa Bazzuu	M	"	"	"	[illegible]
29	Boggalaa Ifaa	M	"	"	"	[illegible]
30	Bajjii Raggaasaa	M	"	"	"	[illegible]
31	Mulu Gurmuu	F	"	"	"	[illegible]
32	Mulu Lataa	F	"	"	"	[illegible]
33	Galaanee Gurbubbaa	F	"	"	"	[illegible]
34	Duddafaa Dirribaa	[illegible]	"	"	"	Duddafa